Rotational Trading using the %b Oscillator

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Introduction

Academic finance is replete with studies supporting or denying the existence of serial correlation in securities prices[1]. In effect, such studies test the weak form efficient market hypothesis (EMH). Simply put, can investors use technical analysis to beat the market?

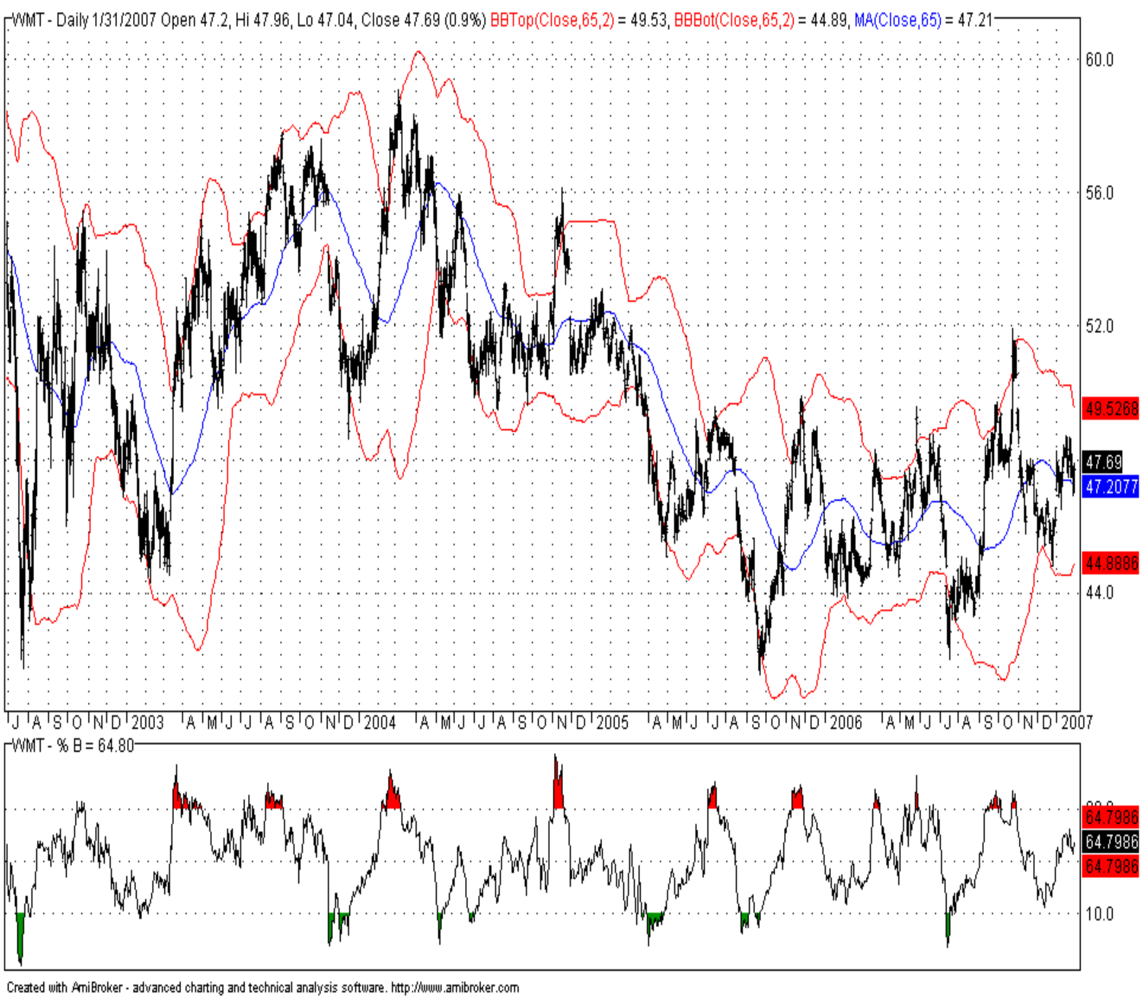
Before we attempt to answer that question, we must define "the market". For purposes of this paper, we define "the market" as the constituent stocks of the S&P 500 Index. The S&P 500 index is, after all, probably the most widely recognized market proxy and in practice, investors index billions of dollars to it. S&P 500 stocks are liquid and extensively researched by a multitude of technical and fundamental analysts. Consequently, one might expect that these stocks would represent a highly efficient segment of the stock market.

Bollinger Bands and the %b Oscillator

%b is a technical indictor derived from the well-known, popular Bollinger Bands indicator. "Bollinger Bands are a technical trading tool created by John Bollinger in the early 1980s. They arose from the need for adaptive trading bands and the observation that volatility was dynamic, not static as was widely believed at the time."[2] Bollinger bands are moving average envelopes typically plotted two standard deviations above and below a moving average of prices. In an end-of-day price chart, %b plots as an oscillator, measuring the closing price in relation to its upper and lower Bollinger Band. An analogous technical indicator is the raw stochastic %k oscillator[3]. Raw %k measures the closing price relative to the high and low price of a trading range of specified length. By definition, %k oscillates between 0 and 100. Zero means the stock closed at the low of the trading range, 100 means the stock closed at the high. Likewise for %b, except that on rare occasions a stock can close with %b below 0 or above 100, representing a two-sigma event. Conceptually, %b numerically identifies the closing stock price relative to its volatility-adjusted trading range.

In Figure 1, we see a price chart for Walmart stock (WMT) covering five years of daily high-low-close prices. In the top pane, we plot a simple 65-day moving average of closing prices represented by the middle blue line. The related Bollinger Bands are plotted in red, exactly two-sigma above and below the middle blue moving average line. In the bottom pane, plot %b is plotted as an oscillator. Here we define %b that is greater than 90 as overbought and %b that is less than 10 as oversold. We highlight overbought %b in red and oversold %b in green.

Figure1.



Rotational Trading

Next, we turn to the concept of rotational trading. Rotational trading is a method of using rank-ordered asset lists to construct investment portfolios. For example, both *Value Line* and *Zacks Investment Research* offer well-known research products featuring proprietary stock timeliness rankings. These services assign a rank, one to five, to each asset in their coverage universe. Using these rankings, a rotational system might buy stocks ranked #1, sell when they drop below rank #2 and rotate those proceeds back into stocks ranked #1. For many years, *Investor's Business Daily* has published proprietary relative strength rankings for stocks ranging from one to ninety-nine. Such increased granularity is useful for active rotational trading, as we will see further on.

As always, a complete trading system must address position sizing: What percentage of total portfolio equity to risk on any given trade or asset.

Portfolio Selection Using Relative %b

The basis for using %b as a momentum oscillator stems from the empirical observation that extreme price excursions have a tendency for mean reversion, i.e. possible negative serial correlation. In *Technical Analysis Explained (Pring, Martin J., McGraw-Hill, 2002),* Martin Pring warned against relying solely on momentum oscillators when analyzing individual securities, "Momentum signals should *always* be used in conjunction with a trend reversal signal by the actual price". We will test the opposite idea but in *a portfolio context.* We will boldly buy weakness and sell strength without waiting for evidence of reversal in price. To mix metaphors, our strategy will systematically "catch the falling knife" and sell the "dead cat" bounce without regard to any other technical indicator. Specifically our trading algorithm buys stocks with the very lowest %b ranks and sells when they increase rank relative to other stocks.

Understand that we will buy a *portfolio of stocks* that have the lowest %b *relative* to all other stocks in a specified selection universe.

In *Technical Analysis from A to Z* (Achelis, Steven B. Chicago: Irwin, 1995), John Bollinger states, "When prices move outside the bands, a continuation of the current trend is implied." Because a reasonable observer could interpret this rule as a contradiction to what we propose to test, we will also consider what happens if we reverse our trading rule, buying strong stocks with the very highest %b (presumably stocks "outside the band") and selling only when they drop in rank.

Now to answer the original question, by using the %b oscillator coupled with rotational trading rules, we can select stock portfolios that beat the risk-adjusted return of the S&P 500 index. We report empirical evidence supporting this thesis later in the results section of this paper. In addition, an important purpose of this paper is to provide sufficient detail to allow other analysts to replicate our (back-test) results and to modify or adapt our methods if desired. That detail comes next in the methods and materials section of this paper.

Methods and Materials

Sample Selection

Acquiring an appropriate sample for back testing proved daunting. Initially we ran some preliminary backtests of our proposed %b indicator on a sample consisting of those stocks in the S&P 500 as of February 2007. This backtest generated very impressive results from 1990 forward. In fact, the results seemed too good to be true. We realized that other analysts could justifiably criticize the backtest sample as suffering from survivor bias[4] and look-ahead bias[5]. Look-ahead bias results from using information in a backtest that was unknown during the period analyzed. Clearly, investors in 1990 had no way to know what stocks would constitute the S&P 500 in 2007. Survivor bias results when a study fails to account for stocks that have ceased trading due to mergers, acquisitions or bankruptcies. Survivor bias also results when for other reasons an index selection committee deletes and replaces a constituent.

What we wanted for our sample was the full history of closing quotes for all stocks that were in the S&P 500 from 1990-2006 during the time those stocks were in the index, including the non-surviving stocks. We were unable to acquire that sample. Instead, we created a sample selection universe using the following protocol. Our sample contains end-of-day-prices for seventeen years, 1990-2006, on S&P 500 constituent stocks. From 1990-1997 we included only stocks that were on the January 1990 S&P 500 constituent list. From 1998-2006 we included prices for all stocks on the January 1998 constituent list. Starting in 2004 for the period 2004-2006, we added all prices for all stocks appearing on the January 2004 constituent list. For all spans and the full period, we included prices of non-surviving stocks up to the date that they ceased trading. Our sample contains 815 stocks, 490 of which were trading at year-end 2006.

Software Tools and Data Services

We downloaded constituent lists for the S&P 500 and prices for inactive, non-surviving stock from the *Bloomberg Professional Terminal*. We downloaded surviving stock price histories from *Yahoo Finance*. We primarily used *Amibroker*[6], a popular technical analysis and charting software application, and the *Amibroker Formula Language* to design and test trading strategies and indicators. We used also Microsoft Excel for various purposes in our study.

Variables, Trading Algorithm, Code

We tested a system based on 65-trading-day (three months) %b against our sample selection universe. At the close of every trading day over the test period, our trading algorithm ranked all stocks from highest to lowest according to %b score. On the first trading day, January 2, 1990, the trading algorithm bought the 40 lowest ranked stocks, investing 2.5% of portfolio equity in each stock. Once purchased, the algorithm held any given stock until it moved up and out of the ranks of the 80 lowest ranked stocks. At that point, the algorithm sold the stock and rotated the proceeds back into one of the 40 lowest ranked stocks not already held. The backtest ended December 31, 2006. The algorithm recorded trade executions at the closing price the next day after order entry. The algorithm continued to execute this rotational trading every trading day of the 17-year backtest period. At the time of purchase, the amount invested in any stock purchase could not exceed 2.5% of current portfolio equity but could be less if available cash was less than 2.5%. There was no rule forcing rebalancing of existing positions. The system traded long only, without margin, and stayed 100% invested. We name this strategy "%b BW" (Buy Weakness). Here is the code in Amibroker Formula Language:

```
//Indicator
PB=100*(C-BBandBot(C,65,2.5)) /
(BBandTop(C,65,2.5)-BBandBot(C,65,2.5));

//Filter
z=IIf(C<1 AND DateNum() >980101,0,1);

//System and Backtest Settings
EnableRotationalTrading();
SetOption("worstrankheld",80);
SetOption("Maxopenpositions",43);
SetOption("allowpositionshrinking",True);
SetOption("holdminbars",4);
PositionSize = -2.5;
PositionScore =  (100 - PB) * z ;
PositionScore = Max( PositionScore, 0 );
```

Variable Initialization and Optimization

Note that in the fourth line of the code we applied a filter. This filter removes stocks from purchase consideration and forces a sale if the stock price was under $1.00 and the date was after January 1, 1998. Although this filter actually reduced system total return, we used it anyway because when inspecting the trade logs we noticed that the system was initiating trades in low price stocks that were no longer in the S&P 500 (though they were at one time). Because our sample price data is split-adjusted, we avoided applying the filter to prices before 1998 since many stocks before that time traded at actual prices much higher than their sub $1.00 split-adjusted price would indicate and were in fact in the S&P 500.

In order to reduce trade activity, we also required the algorithm to hold a stock at least four trading days before selling (SetOption("holdminbars",4)). We chose 65-day %b, 80-rank "worst rank held", and 2.5% position size without rigid optimization for maximum total return or any other specific outcome. In our judgment, system performance was reasonably robust across a relevant range of optimization values.

Our reported backtest results assume a .1% cost per trade (.2% round-trip). We noticed that very short (5-20 day) %b BW backtested impressively with a 0% assumed cost but performance degraded dramatically when tested with a .1% cost per trade.

We also tested our rule in reverse by changing the second to last line of the code to from – PB to + PB. We name this strategy “%b BS” (Buy Strength) since it buys strong stocks with high relative %b. Recall that high %b means that a stock price is near or above its top Bollinger Band.

Results

Table 1 presents the results of our backtests on the custom sample described previously. The first column represents a buy and hold strategy on the S&P 500 price index over the backtest period. The second column tests our proposed strategy, %b BW. The final column tests the %b BS Strategy.

Table 1. 1990-2006 Backtest Results* (excludes dividends)

	Buy and Hold S&P 500	**%b BW (Buy Weakness)**	**%b BS (Buy Strength)**
Initial capital invested	$100,000	$100,000	$100,000
Ending capital	$401,329	$3,909,757	$142,890
Total Return	301%	3809%	43%
Annualized Total Return	8.50%	24.10%	2.10%
Annualized Standard Deviation	15.90%	17.70%	-
Sharpe Ratio	0.35	1.19	-
Annualized Alpha vs. S&P 500	0	13.89	-
Tracking Error	0	12.04	-
Information Ratio	0	1.15	-
Total # of trades	1	13,778	17,166
Average Trades per Day	0	3.2	4
Average Net Profit per Trade	301%	1.20%	0.11%
Average # of Trading Days Held	4288	14.37	11,64
% of Total Trades Profitable	-	65.20%	41.70%
Worse loss on a single trade	-	-98.30%	-98.20%
Maximum system % drawdown	49.20%	-33.40%	46.00%
Applied % transaction costs per trade	0.00%	0.10%	0.10%

*A similar backtest of %b BW on our initial biased sample (the current S&P 500 constituents) generated annualized total return of 31.6%; %b BS generated annualized total return of 3.2%. We provide this information as an example of the potential effects of sample bias on reported system performance. Also, note that the pronounced difference in total return between the two strategies appears to be relatively consistent regardless of the sample.

Figure number two is a profit distribution histogram of all trades executed by the %b BW (Buy-Weakness) Strategy over the 17 years back-test period. Table 2 lists the fourteen trades returning the extreme losses in the histogram.

Figure 2. Profit Distribution Histogram of 13,788 trades, %b BW Strategy, 1990 -2006

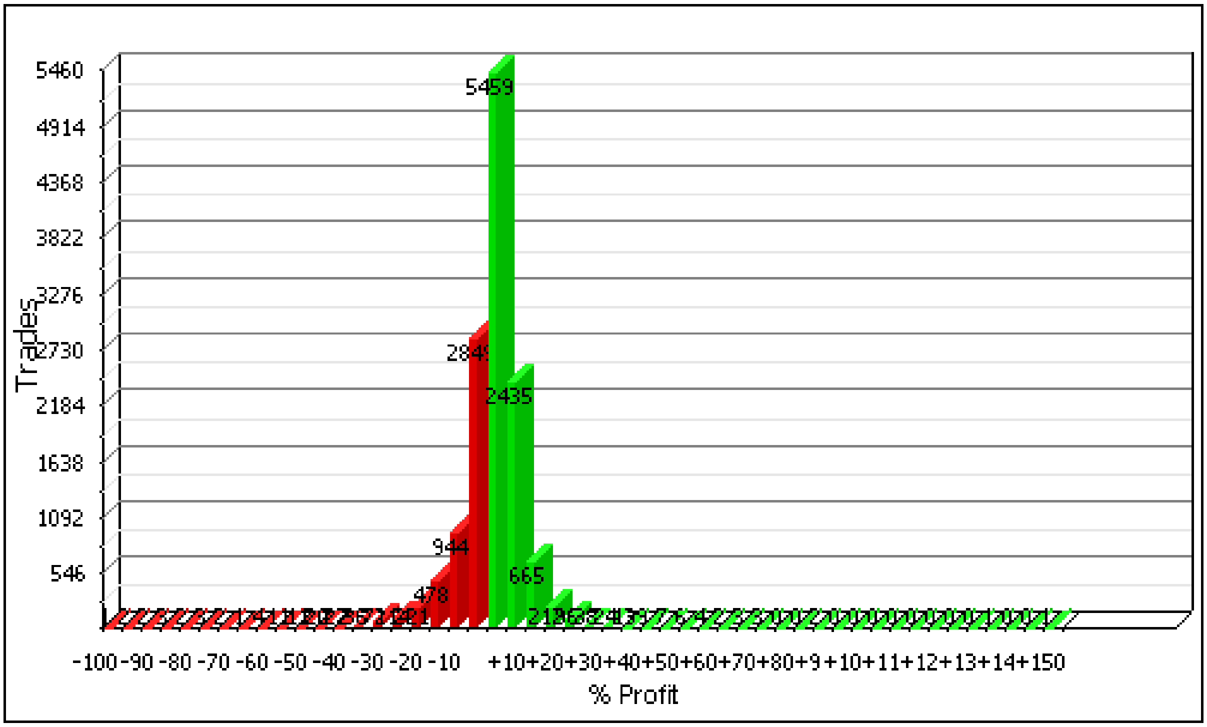
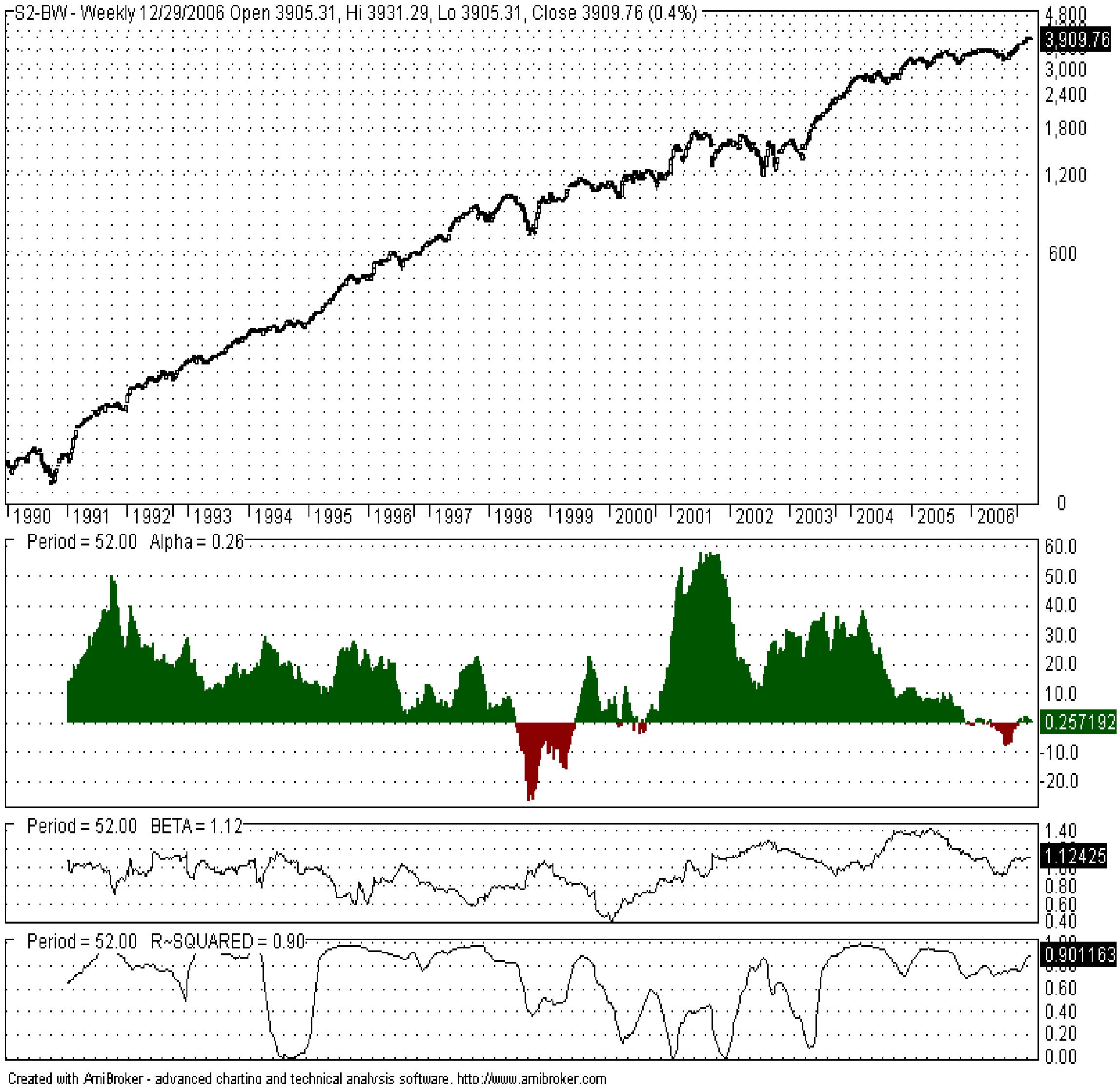


Table 2. The 14 largest losers of 13,788 trades,%b BW Strategy 1990-2006

Ticker	Asset Description	Date Bought	Price	Date Sold	Exit Price	% loss
ENRNQ UN Equity	ENRON CORP	10/23/2001	19.79	11/29/2001	0.36	-98.18%
ACKH UN Equity	ARMSTRONG HOLDINGS INC	9/15/2000	14.0625	11/30/2000	0.9375	-93.33%
DPHIQ	DELPHI CORP	9/12/2005	4.21	10/11/2005	0.36	-91.45%
WCOEQ UQ Equity	WORLDCOM GROUP	1/22/2002	12.28	5/30/2002	1.67	-86.40%
KMRTQ UN Equity	KMART CORP/OLD	12/5/2001	6.26	1/23/2002	0.89	-85.78%
DCNAQ UN Equity	DANA CORP	1/18/2006	4.84	3/6/2006	0.76	-84.30%
WAN/B UA Equity	WANG LABORATORIES - B	7/27/1992	2.75	9/24/1992	0.44	-84.00%
SGID UN Equity	SILICON GRAPHICS INC	4/24/2001	2.6	7/11/2001	0.51	-80.38%
KMRTQ UN Equity	KMART CORP/OLD	2/28/1995	12.75	3/22/1995	3	-76.47%
CPNLQ	CALPINE CORP	11/7/2005	2.04	11/30/2005	0.51	-75.00%
DALRQ UN Equity	DELTA AIR LINES INC	7/28/2005	2.85	9/13/2005	0.78	-72.63%
ETS UN Equity	ENTERASYS NETWORKS INC	2/5/2002	32	4/30/2002	8.8	-72.50%
NOVL	NOVELL INC	3/29/2000	28.88	6/2/2000	8.59	-70.26%
NT	NORTEL NETWORKS CORP	2/14/2002	57.2	6/4/2002	18	-68.53%

The top pane in Figure number three plots the weekly closing value for a unit of equity in the %b BW system. The lower panes plot rolling 52-week Alpha*, Beta and R-squared on the closing value vs. the benchmark S&P 500 from 1990-2006.

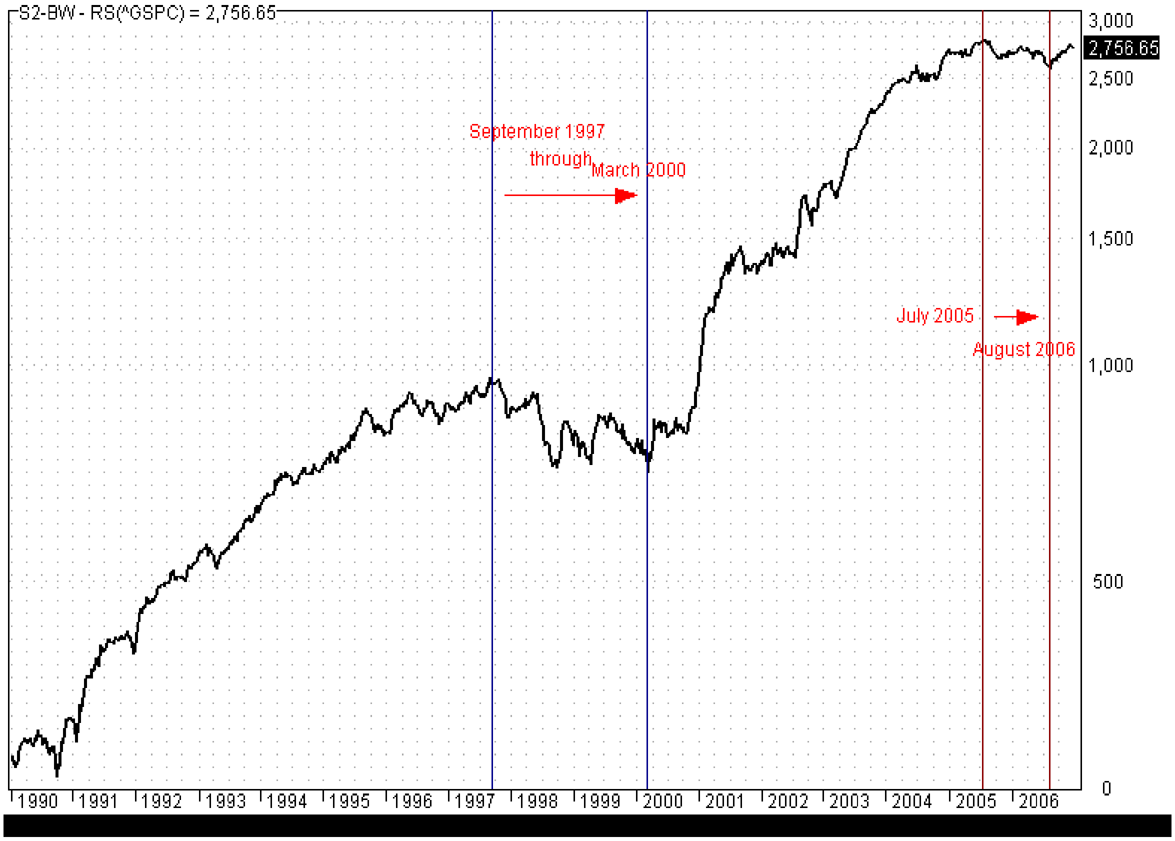
Figure 3.



*We calculate the alpha depicted in Figure 3 differently than the alpha reported in Table 1. The alpha in Figure 3 is a linear regression estimate modeled as Strategy Return = alpha + Beta(Return on the S&P 500). The alpha reported in Table 1 is the annualized mean difference of paired comparisons on 4287 observations of daily returns on the S&P 500 versus a unit of equity in the % BW strategy.

Figure number four plots a weekly comparative relative strength line[8] from 1990-2006 of the %b BW strategy using the S&P 500 Price Index as the base price. We delineate two major periods of relative underperformance.

Figure 4.



Tests of Statistical Significance

Is the difference in return between the %b BW strategy and the S&P 500 statistically significant? To answer that question, we used a paired comparisons test of 4287 paired differences in daily returns from 1990-2006. The sample mean difference was .0533% per day (the mean daily alpha). The sample standard deviation of the mean difference was .7462% (the daily tracking error). The standard error of the sample mean difference was .7462% * 4287^.5 = .0114%. The calculated test statistic was z = (.0533/.0115) = 4.68. The two-tailed P value is less than 0.0001. The difference in returns is extremely statistically significant.

Is the *risk-adjusted* return of the %b trading strategy statistically significant? The Information Ratio[8], also known as the appraisal ratio, is a widely used risk metric that measures risk and return relative to an appropriate benchmark. The information ratio equals alpha divided by tracking error. We tested to determine if the information ratio (IR) of the %b strategy was greater than zero:

$$t - statistic = IR \bullet \sqrt{T}$$

Where T is the number of years.

From Table 1 we see the information ratio for the %b strategy equaled 1.15. So our test statistic is t = 1.15 * 17^.5 = 4.74 with df =16. The two-tailed P value equals 0.0003. The difference is extremely statistically significant.

Discussion

The evidence supports our thesis that a rotational trading algorithm using relative %b rankings can select stock portfolios that beat the risk-adjusted return on the S&P 500. Moreover, those portfolios consist only of S&P 500 constituent stocks. For perspective, a search of the expansive *Morningstar* mutual fund database in February 2007 reveals that just three mutual funds had an annualized rate of return in excess of 18% over the past fifteen years. None of those returns exceeded 19%. The %b BW Strategy* returned 24.1% annualized with surprisingly little risk relative to the benchmark. The charts in Figures 3 and 4 as well as the Sharpe and Information Ratios reported in Table 1 provide the relevant risk assessment analytics.

Admittedly, we have presented backtest results that fly in the face of the well-worn trader's axiom "Cut your losses short; let your profits run". Table 2 confirms that the %b BW system offers no protection against ruinous losses at the asset level. The

*The historical performance of a simulated trading strategy is not a guarantee of future returns.

diversification of an equal-weight 40 stock portfolio afford the only down side protection, a striking demonstration of the critical importance of position sizing and diversification in system development.

While our results are statistically significant, the economic significance is less straightforward. The system trades frequently averaging over three trades per day. For taxable investors, returns would be taxed 100% as unfavorable short-term capital gains. From Table 1 we see the average profit per trade is 1.2% net of an assumed .2% round trip transaction costs. That is likely satisfactory only for a trader using an efficient broker[9] and perhaps more importantly, trade size must be sufficiently small to have only a modest impact on market prices. Assessing potential slippage[10] is clearly an important consideration when evaluating any system.

Finally, the results suggest that investors overreact, possibly to news or changing prices, in a three-month (65- trading day) frame of reference. By design, our indicator look-back period corresponds with the three-month earnings report cycle for stocks as well as the performance reporting cycle for many asset managers capturing possible earnings-announcement and window dressing[11] effects.

End Notes

1 http://serial-correlation.behaviouralfinance.net/ retrieved from the web February 2006.

2 http://www.bollingerbands.com/ retrieved from the web February 2006.

3 http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators:stochastic_oscillato retrieved from the web February 2006

4 http://en.wikipedia.org/wiki/Survivorship_bias retrieved from the web February 2006.

5 http://www.investopedia.com/terms/l/lookaheadbias.asp retrieved from the web February 2006.

6 http://amibroker.com/ retrieved from the web February 2006.

7 http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators:price_relative retrieved from the web February 2006.

8 http://www.ssga.com/library/esps/sflanneryinfowhitenoisega/page.html retrieved from the web February 2006.

9 http://www.interactivebrokers.com/en/accounts/fees/commission.php?ib_entity=llc#bundled retrieved from the web February 2006.

10 http://www.investopedia.com/terms/s/slippage.asp retrieved from the web February 2006.

11 http://www.investopedia.com/terms/w/windowdressing.asp retrieved from the web February 2006.