

Purified Sentiment Indicators

For The

Stock Market

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Abstract

We attempt to improve the stationarity and predictive power of stock market sentiment indicators (SI) by removing the influence of the market's recent price dynamics (velocity, acceleration & volatility). We call the result a purified sentiment indicator (PSI). PSI is derived with an adaptive regression model employing price dynamics indicators to predict SI. PSI is the difference between observed SI and predicted SI normalized by model error. We produce PSI for the following SI: CBOE Implied Volatility Index (VIX), CBOE Equity Put to Call Ratio (PCR), American Association of Individual Investors Bulls minus Bears (AAII), Investors Intelligence Bulls minus and Bears (INV) and Hulbert's Stock Newsletter Sentiment Index (HUL). All SI series are predictable from price dynamics (r-squares range from .25 to .70). Using cross-validation we derive a signaling rule for each SI, PSI, and price dynamics indicator and compare them with a random signal in terms of their out-of-sample profit factor (PF) trading the SP500. Purification generally improves the stationarity of SI by reducing drift and stabilizing variability. However, it generally reduces PF for PCR, AAII, INV and HUL suggesting at least some of their predictive power stems from price dynamics. In contrast, PF of VIX is significantly enhanced by purification implying it contains predictive information above and beyond price dynamics but which is masked by price dynamics. Purified VIX is superior to all other indicators tested.

I. Background

A. Sentiment Indicators

Technical analysts use SI to gauge the expectations of various groups of market participants, predict market trends and generate buy & sell signals under the assumption that they carry information that is not redundant of price indicators. SI are interpreted on the basis of *Contrary Opinion Theory* which suggests that if investors become too extreme in their expectations,

the market will subsequently move opposite to the expectation. Thus, extreme levels of optimism (pessimism) should precede market declines (advances).

There are of two types of SI: direct and indirect. Direct indicators poll investors in a particular group, such as individual investors (AAII) or writers of newsletters (INV & HUL) about their market expectations. Indirect indicators (PCR & VIX) infer the expectations of investors in a particular group by analyzing market statistics that reflect the group's behavior. For example, put and call option volumes reflect the behavior of option traders. Thus an abnormally high ratio of put to call volume would imply options traders expect the market to decline.

B. Prior Research

Influence of Market Dynamics

Our study is motivated by three areas of prior research: (1) influence of market dynamics on sentiment indicators, (2) predictive power of sentiment indicators and (3) use of regression analysis to purge indicators of unwanted effects in an effort to boost their predictive power.

With respect to (1), intuition alone would suggest that sentiment should be influenced by the market's recent behavior. A down (up) trend should fuel pessimism (optimism). This is supported by studies demonstrating that people suffer from an availability bias, the tendency to overestimate the probability of an event which is easily brought to mind due to recency or vividness. Thus, investors would likely overestimate the probability that a recent trend will continue. Empirical support can be found in Fosback (1976), Solt & Statman (1988), De Bondt (1993), Clarke and Statman (1998), Fisher and Statman (2000), Simon and Wiggins (2001), Brown & Cliff (2004) Wang, Keswani & Taylor (2006).

Tests of Predictive Power

Tests of SI predictive power are numerous but inconsistent. However, because the studies consider different SI, historical periods, and evaluation metrics, a firm conclusion is difficult.

Two evaluation methods have been used: correlation and the profitability of rule-based signals. Correlation quantifies the strength of the relationship between sentiment and the market's future return in terms of r-squared, which is the percentage of the variation in return that is predicted by the SI. The signal approach measures the financial performance of sell (buy) signals given when the indicator crosses a threshold indicating excessive optimism (pessimism). Here a useful metric is the profit factor, the ratio of gains from profitable signals to losses from unprofitable signals. It implicitly takes into account the fraction of profitable signals and the average size of wins and losses. Values above 1.0 indicate a profitable rule, while values less than 1.0 indicate an unprofitable rule. Because market conditions over a given test period can profoundly impact the profit factor, an important benchmark for comparison is the profit factor of a similar number of random signals over the same time period.

Using both methods, Fosback (1976) tests numerous sentiment indicators on data from 1941 through 1975, finding that some are predictive individually and conjointly when used in multiple-regression models. Solt & Statman (1988) test INV from 1963 to 1985 and find no predictive power, and attribute a pervasive belief in INV's efficacy to cognitive errors (confirmation bias and erroneous intuitions about randomness). Clark & Statman (1998) use an additional ten years of data and confirm INV's lack of utility. Fisher & Statman (2000) confirm this result but find that AAI is predictive. They use multiple regression to combine several SI and obtain an r-squared of 0.08 which has economic value in market timing. Simon & Wiggins (2001) use data from 1989 to 1998 to show that VIX and S&P100 option put-to-call ratio are statistically significant predictors of S&P500 over 10 to 30 days forward and derive an effective signaling rule. They conclude the SI examined frequently have statistically and economically significant predictive value. Hayes (1994) combines stock market sentiment with that of gold and treasury bonds to form a composite SI for

stocks and finds rule-based signals that are useful. In contrast, Brown and Cliff (2004) tested ten SI observed monthly from 1965 to 1998, and weekly from 1987 to 1998 and find that used individually or combined they have limited ability to predict near-term market returns. Wang, Keswani & Taylor (2006) test OEX put-to-call volume ratio, OEX put-to-call open interest ratio, AAI and INV using regression and find no predictive power. Clearly, the evidence is mixed.

Regression Modeling for Indicator Purification

Indicator purification via regression modeling is introduced by Fosback (1976). He finds sentiment of odd-lot short sellers and mutual fund managers is predictable and that they have enhanced forecasting significance when they deviate from predicted levels. The Fosback Index (FI) is the deviation of mutual fund cash-to-asset ratio (CAR) from a regression model's prediction based on short-term interest rates. FI signals are superior to CAR. Goepfert (2004) applies Fosback's method to more recent data, confirming the relation between short-term interest and CAR (r-squared 0.55) and the potency of FI signals.

Merrill (1982) uses regression to remove the effect of beta from a stock's relative strength ratio (RS). A limited test shows purified RS signals are superior to those obtained from traditional RS. Jacobs and Levy (2000), use multiple regression to purify 25 fundamental and technical indicators and demonstrate that the purified indicators have improved predictive power and independence. Stonecypher (1988) derives an "available liquidity" indicator, the deviation of stocks prices from a regression prediction based on mutual fund cash, credit balances and short interest.

C. How This Paper Extends Prior Research

Our research extends prior research in several ways. First, we apply regression purification to five SI not previously treated in this manner. Second, while prior studies use static regression models, ours is adaptive, with periodic refitting to allow changing indicators and indicator weights to capture changes in the linkage between market dynamics and

sentiment. Third, while prior studies have established the link between price velocity and SI, our study also considers acceleration and volatility. Fourth, unlike prior studies using regression for purification, we normalize the deviation between observed and predicted sentiment by the model's standard error, thus producing an indicator with more stable variance. Fifth, prior efforts to reduce drift and stabilize the variability of SI use the trend and variability of the SI itself. Instead we use the stock market's price dynamics because of their established influence on sentiment.

II. Analysis Procedure

A. Sentiment Indicators Analyzed

American Association of Individual Investors Sentiment Survey (AAII): July 27, 1987 to October 31, 2008, published weekly. Source Ultra Financial Systems (www.ultrafs.com)

Investors Intelligence Advisor Sentiment Bulls - Bears (INV): January 4, 1963 to October 31, 2008, published weekly by Investor's Intelligence.

Hulbert Stock Newsletter Sentiment Index (HUL): January 2, 1985 to October 31, 2008, published weekly, is the average recommended stock market exposure for a subset of short-term market timers tracked by the Hulbert Financial Digest. Source: Mark Hulbert.

CBOE Equity Put to Call Volume Ratio (PCR): October 1, 1985 through October 31, 2008. Series includes ETF options. Source: Luthold Group.

CBOE Implied Volatility Index (VIX): January 2, 1986 through October 31, 2008. It is an indicator of the implied volatility of SP500 index options. Prior to 2003 it was based on S&P100 options. Source: Ultra Financial Systems (www.ultrafs.com).

B. Method Used To Derive Purified Sentiment Indicators

The conceptual basis of our purification method is seen in Figure 1, a scatterplot of velocity (price dynamics) versus a sentiment indicator. Each point on the plane is a combination of sentiment and velocity.

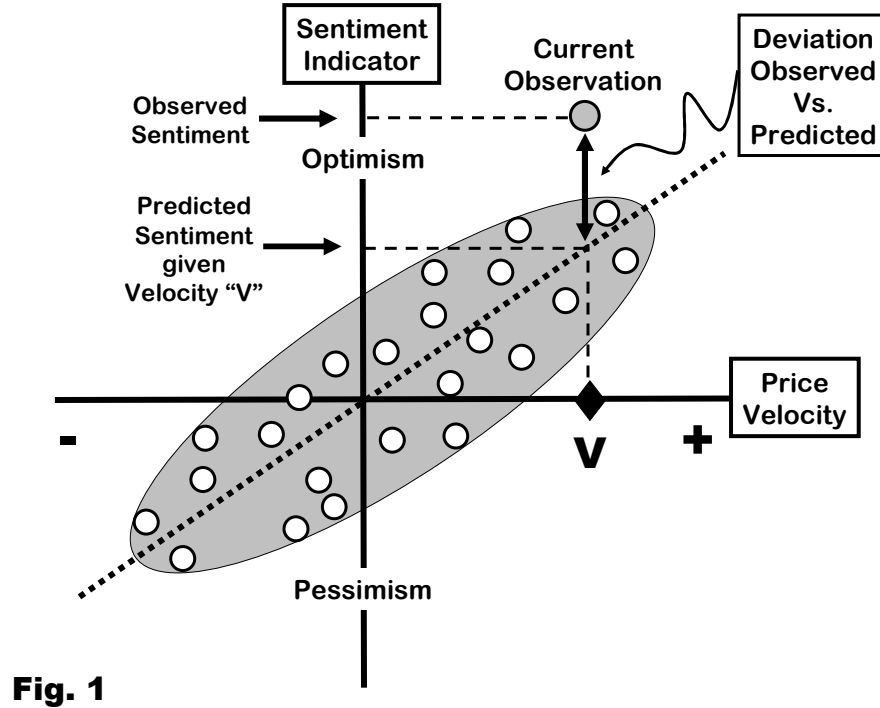


Fig. 1

The elongated cloud of points is the window of recent observations used to fit the regression model relating sentiment to price velocity. The dotted line is the model's predicted value of sentiment for each value of velocity. For example, given velocity "V" on the horizontal axis, the model would predict the level of sentiment indicated on the vertical axis. However, current observed sentiment (large dot) is greater than the predicted value (i.e. excessive optimism). The vertical deviation from the regression line when divided by a measure of the degree of spread of the points around the line (standard error) is *purified sentiment* or sentiment net of price dynamics.

Our model, which uses two indicators of price dynamics to predict sentiment, is portrayed in Figure 2. The model's predictions are represented by the grey plane.

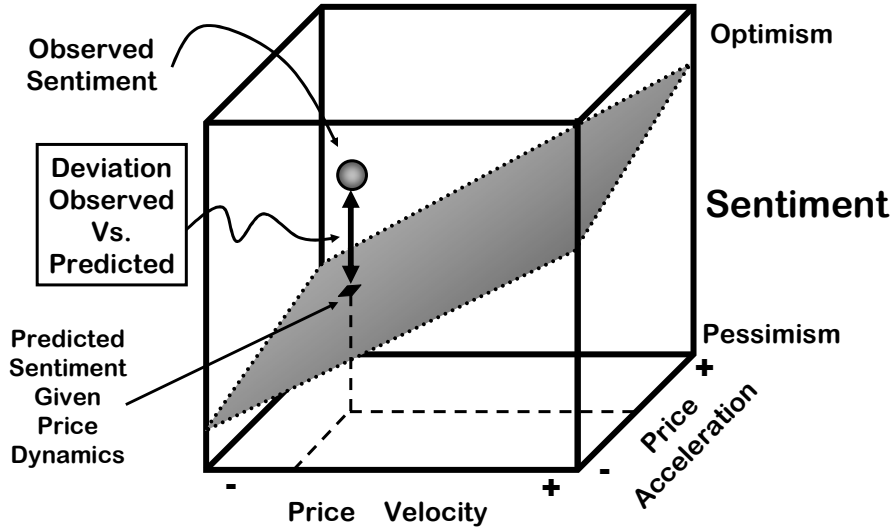


Fig. 2

The model uses a moving data window comprising the 300 most recent observations. This window is referred to as a *fold*.

The model is adaptive in two ways. First, every 10th day the model's indicator weights are allowed to change to reflect possible changes in the relationship between price dynamics and sentiment. The weights determine the inclination of the plane. Second, every 100th day we allow the pair of price dynamics indicators used in the model to change. This allows it to capture the evolving relationship between sentiment and price dynamics. The pair that provides the best fit (r-squared) to 300 days of data in the current fold is selected from a set 18 candidates described below and is retained until indicator selection takes place again 100 days hence. Given the historical data used, this procedure allows for a total of 48 folds each overlapping the two nearest folds by 200 days. All 153 possible pairs ($18 \times 17 / 2$) are evaluated to select the best. The parameters (300, 10, 100) were selected arbitrarily based on intuition and are likely not optimal. In the results section we show how frequently each of the 18 indicators

was selected as a member of the best pair (percent of 48 folds in which the indicator was selected).

The 18 candidate price dynamics indicators are of 3 types: velocity, acceleration and volatility, with six variants of each type. The variants differ with respect to the number of days used to measure velocity and acceleration or with respect to the exponential smoothing constant used to measure volatility. Type 1 (price velocity) is the slope term of a moving linear regression, fit using least squares, to the logs of the S&P500 close. The six fitting or look-back periods are 11, 22, 44, 65, 130 and 260 days. Specifically, we define price velocity as the coefficient “b” in the function $y = a + bx$, where y is the log of price and x is the date index (increasing by one for each trade date). Type 2 (price acceleration or curvature) is the second order term of a moving parabolic regression, fit using least squares to the logs of the S&P500 close using fitting periods of 11, 22, 44, 65, 130 and 260 days. Thus acceleration is the “c” coefficient in the function $y = a + bx + cx^2$ where y is the log of price and x is the date index. Type 3 (price volatility) is the exponentially smoothed absolute value of the daily percentage change in the SP500 close, using smoothing constants of 0.1666, 0.0870, 0.0444, 0.0303, 0.0154, 0.0077, which approximate moving averages of 11, 22, 44, 65, 125 and 260 days respectively. For a listing of the 18 price dynamics indicators see Table 1 below.

Table 1: 18 Price Dynamics Indicators

	Type	Indicator Description
1	Velocity	Linear Slope 11 days
2	Velocity	Linear Slope 22 days
3	Velocity	Linear Slope 44 days
4	Velocity	Linear Slope 65 days
5	Velocity	Linear Slope 130 days
6	Velocity	Linear Slope 260 days
7	Acceleration	Parabolic Curvature 11 days
8	Acceleration	Parabolic Curvature 22 days
9	Acceleration	Parabolic Curvature 44 days

10	Acceleration	Parabolic Curvature	65 days
11	Acceleration	Parabolic Curvature	130 days
12	Acceleration	Parabolic Curvature	260 days
13	Volatility	Expo. Smoothed % change	m.a. approx. 11 days
14	Volatility	Expo. Smoothed % change	m.a. approx. 22 days
15	Volatility	Expo. Smoothed % change	m.a. approx. 44 days
16	Volatility	Expo. Smoothed % change	m.a. approx. 65 days
17	Volatility	Expo. Smoothed % change	m.a. approx. 130 days
18	Volatility	Expo. Smoothed % change	m.a. approx. 260 days

PSI for a given date is the deviation of observed SI from the model's predicted SI value given the values of the price dynamics indicators in the regression model as of that date, divided by model's standard error as of that date. When the model is less predictive (i.e. larger standard errors) the divisor is larger, thus reducing the PSI value. This lends greater uniformity to the variability of purified sentiment over time, an important feature for threshold-based signaling rules.

Using this approach we derive daily values for purified sentiment indicators for five SI: AAIL, INV, HUL, PCR, and VIX. Although AAIL, INV, HUL are weekly series, we produce daily values by holding the most recently known weekly value constant until a new value is available. To avoid look-ahead bias, the data is dated as of the time it is known by investors.

C. SI and PSI Tested for Signal Performance

From the five sentiment series (AAIL, HUL, INV, PCR & VIX) we derive 50 indicators: 25 SI and 25 PSI. Using AAIL as an example: [1]AAIL no smoothing, [2], [3], [4] and [5] are exponentially smoothed versions of AAIL using smoothing constants (simple moving average equivalent) of 0.1666 (11), 0.0870 (22), 0.0444 (44), 0.0303 (65), [6] purified AAIL no smoothing, [7], [8], [9] and [10] exponentially smoothed versions of [6] using the smoothing constants just mentioned. The 50 indicators are listed in Table 2.

Table 2.

Number	Description
1	AAII no smoothing
2	AAII Expo. Smooth 11 day (0.1666)
3	AAII Expo. Smooth 22 day (0.0870)
4	AAII Expo. Smooth 44 day (0.0444)
5	AAII Expo. Smooth 65 day (0.0303)
6	AAII Purified no smoothing
7	AAII Purified Exp. Smooth 11 day (0.1666)
8	AAII Purified Exp. Smooth 22 day (0.0870)
9	AAII Purified Exp. Smooth 44 day (0.0444)
10	AAII Purified Exp. Smooth 65 day (0.0303)
11	INV no smoothing
12	INV Expo. Smooth 11 day (0.1666)
13	INV Expo. Smooth 22 day (0.0870)
14	INV Expo. Smooth 44 day (0.0444)
15	INV Expo. Smooth 65 day (0.0303)
16	INV Purified no smoothing
17	INV Purified Exp. Smooth 11 day (0.1666)
18	INV Purified Exp. Smooth 22 day (0.0870)
19	INV Purified Exp. Smooth 44 day (0.0444)
20	INV Purified Exp. Smooth 65 day (0.0303)
21	HUL no smoothing
22	HUL Expo. Smooth 11 day (0.1666)
23	HUL Expo. Smooth 22 day (0.0870)
24	HUL Expo. Smooth 44 day (0.0444)
25	HUL Expo. Smooth 65 day (0.0303)
26	HUL Purified no smoothing
27	HUL Purified Exp. Smooth 11 day (0.1666)
28	HUL Purified Exp. Smooth 22 day (0.0870)
29	HUL Purified Exp. Smooth 44 day (0.0444)
30	HUL Purified Exp. Smooth 65 day (0.0303)
31	PCR no smoothing
32	PCR Expo. Smooth 11 day (0.1666)
33	PCR Expo. Smooth 22 day (0.0870)

34	PCR Expo. Smooth 44 day (0.0444)
35	PCR Expo. Smooth 65 day (0.0303)
36	PCR Purified no smoothing
37	PCR Purified Exp. Smooth 11 day (0.1666)
38	PCR Purified Exp. Smooth 22 day (0.0870)
39	PCR Purified Exp. Smooth 44 day (0.0444)
40	PCR Purified Exp. Smooth 65 day (0.0303)
41	VIX no smoothing
42	VIX Expo. Smooth 11 day (0.1666)
43	VIX Expo. Smooth 22 day (0.0870)
44	VIX Expo. Smooth 44 day (0.0444)
45	VIX Expo. Smooth 65 day (0.0303)
46	VIX Purified no smoothing
47	VIX Purified Exp. Smooth 11 day (0.1666)
48	VIX Purified Exp. Smooth 22 day (0.0870)
49	VIX Purified Exp. Smooth 44 day (0.0444)
50	VIX Purified Exp. Smooth 65 day (0.0303)

D. Profit Factor Evaluation of Indicators

We evaluate SI and PSI and price dynamics indicators in terms of PF realized from long and short positions in the SP500 rather than their correlation with SP500 future returns. Although Clarke et al. (1989) show that a significant correlation implies favorable financial performance from a timing strategy, the converse is not true. An insignificant correlation does not necessarily imply poor financial performance. Thus, while correlation can fail to detect indicators able to deliver good financial performance, the prime concern of investors, PF explicitly measures it.

Because PF is computed from signal outcomes, a signaling rule must be defined. We define 100 sentiment based signaling rules, one long and one short for each of the 25 SI and 25 PSI. In addition, to measure the predictive power of price dynamics, we define 36 signaling rules based on the 18 price dynamics indicators (Table 1). Thus the 18 price dynamics

indicators play two roles in this study. They are used to predict and thus purify sentiment. They are also used for signaling rules to trade the SP500.

Signals occur when the indicator crosses a threshold. We use a cross-validation procedure to establish the signal threshold in-sample and measure the rule's PF performance the out-of-sample. Our procedure is to segment the historical data, 1990/01/01 to 2008/10/31, by calendar year into 19 chunks. In turn, each year is held aside as out-of-sample data (OUT) while the remaining 18 years are treated as in-sample (IN). IN is used to search for two signal thresholds, one that maximizes buy-signal PF and one that maximizes sell-short-signal PF. We then apply these thresholds to OUT to obtain signal outcomes. This procedure is performed a total of 19 times, withholding a different year each time as OUT. A separate PF long and a PF short is then computed from a concatenation of the OUT signals. Thus each rule is characterized by two figures of merit, long PF OUT and short PF OUT. The procedure of using IN to optimize a rule and OUT to evaluate its performance is called cross validation. It has the advantage of providing a nearly unbiased estimate of rule performance in different data. In contrast, evaluating a rule in the same data that was also used to construct or optimize the rule is known to give optimistically biased estimates of its performance in different data.

Our procedure enters a long or short position in SP500 on the opening price of the day following a signal and liquidates the position on the following opening price. If the signal is still in effect on the following day (indicator remains beyond threshold) a new position is established at the open (the same price at which a position was just liquidated). This ensures the independence of signal outcomes, a requirement for significance testing. We test the null hypothesis that the buy rule's (sell-short rule's) PF is no better than that of a random signal taking the same number of positions. In Figures 19 – 34 we highlight PF for all rules that are significant at the 0.05 level. The distribution of PF, if the null hypothesis were true, is generated with a Monte-Carlo permutation test with 1000 replications. This distribution represents the random variation one would expect in PF for a rule with no predictive power. If the PF of the

rule tested is greater than 950 of the 1000 replications (i.e., only 50 have higher PF) the rule is judged to be statistically significant.

Because we test 136 rules, including the 36 buy and sell rules based on the 18 price dynamics indicators, listed Table I, we would expect a certain number to appear significant by chance. Note that it is possible for a rule with a lower PF to be more significant than another rule with a higher PF when the latter has a smaller number of signals. Significance depends on both PF achieved and the number of signals allowed by the threshold.

III. Results

A. How Predicable Is Sentiment from Price Dynamics?

Figure 3a shows how well the two-indicator regression model was able to predict each SI. The r-squared is the average over 48 folds, each comprised of 300 observations, with a 200-observation overlap between folds. Note there are two sources of upward bias in the r-squared values reported in Figure 3a. First, the selection of a best pair of price dynamics indicators from 153 possible pairs there creates an upward bias. Second, there is an upward bias for its being an in-sample regression fit. For this reason we show in Figure 3b shows the average r-squared of all pairs tested (153 x 48).

Predictability of Sentiment by Price Dynamics R² of Regression Model (Best Pair)

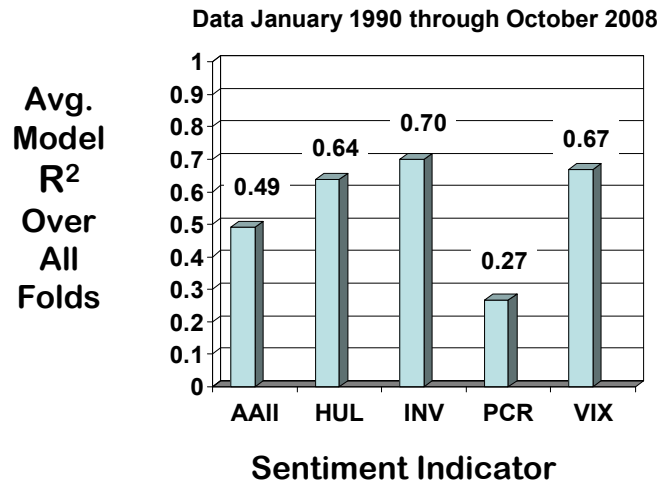


Fig. 3a

Predictability of Sentiment by Price Dynamics R² of Regression Model (All Pairs Tested)

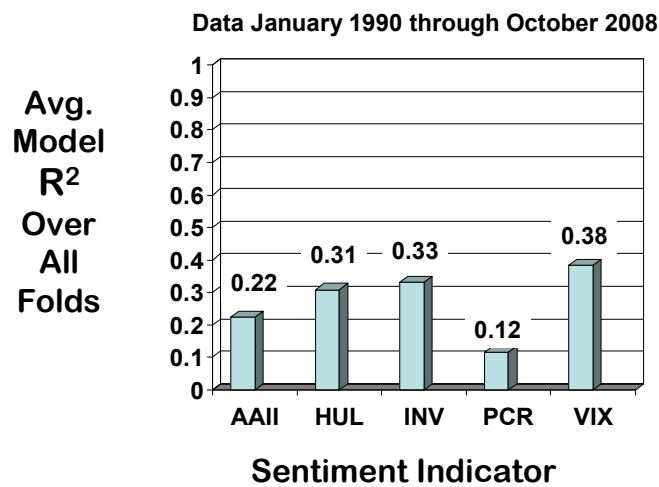
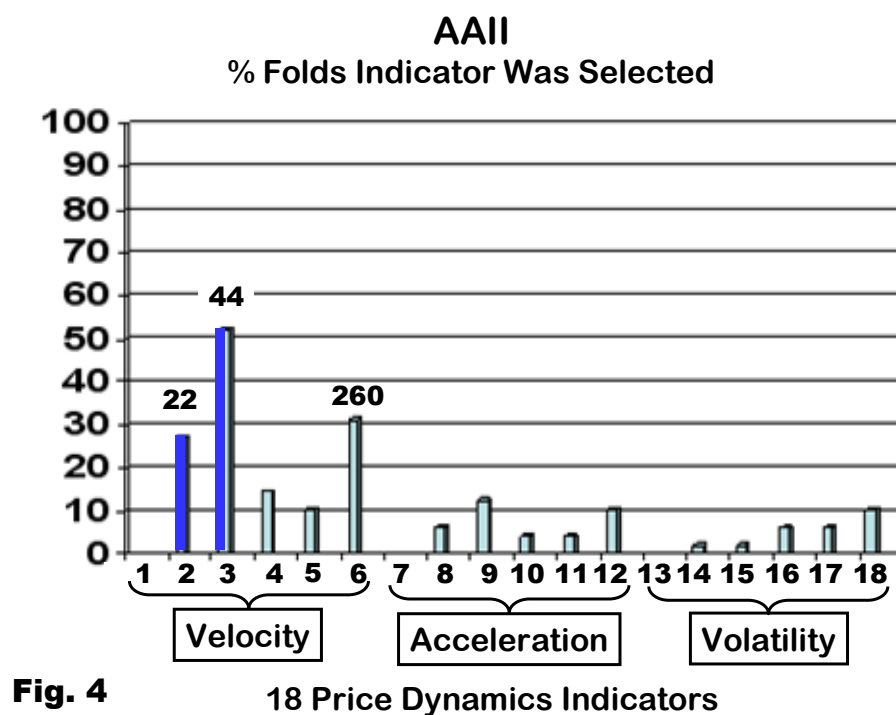


Fig. 3b

B. Relative Importance of 18 Price Dynamics Indicators in Predicting Sentiment

Figures 4 through 8 show the relative importance of the 18 price dynamics indicators in predicting each of the five sentiment indicators. The importance of each indicator is given in terms of the percentage of folds (48) the indicator was selected as a member of the best pair used in the regression model. The look-back span for the most frequently used indicators is supplied for convenience. If the indicator's regression weight has the same algebraic sign (always + or always -) across all folds in which it was used, its bar is colored dark blue.



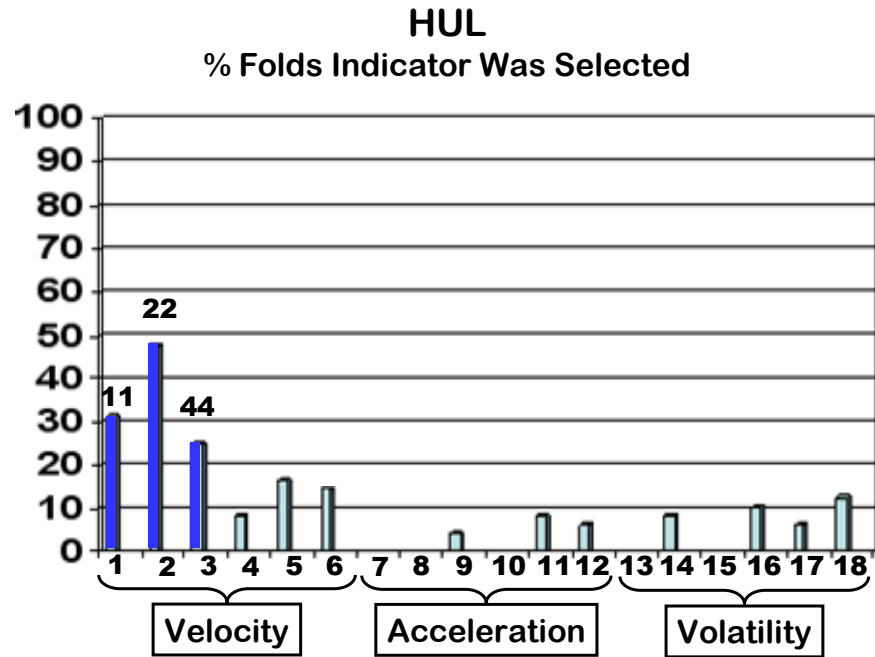


Fig. 5 18 Price Dynamics Indicators

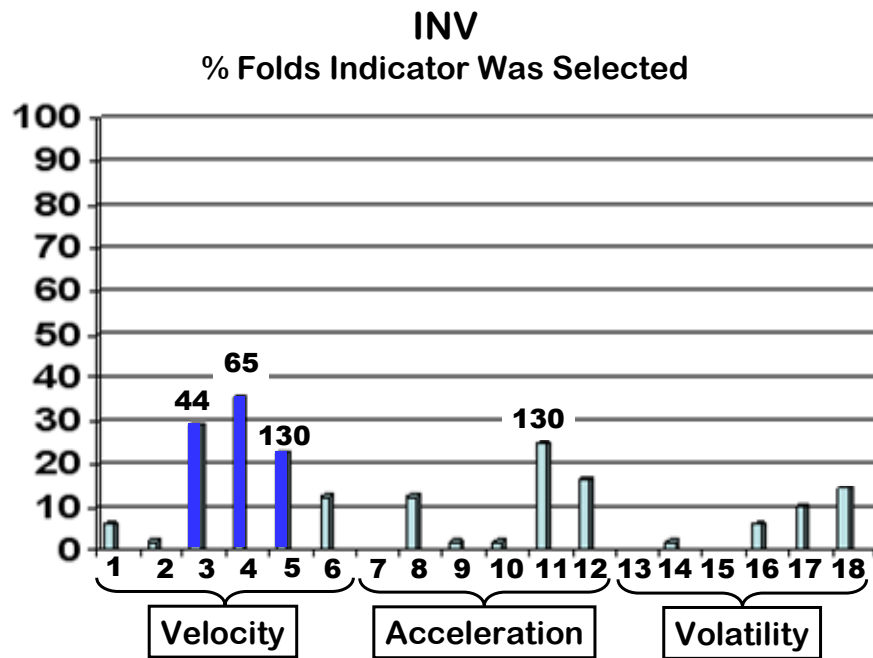


Fig. 6 18 Price Dynamics Indicators

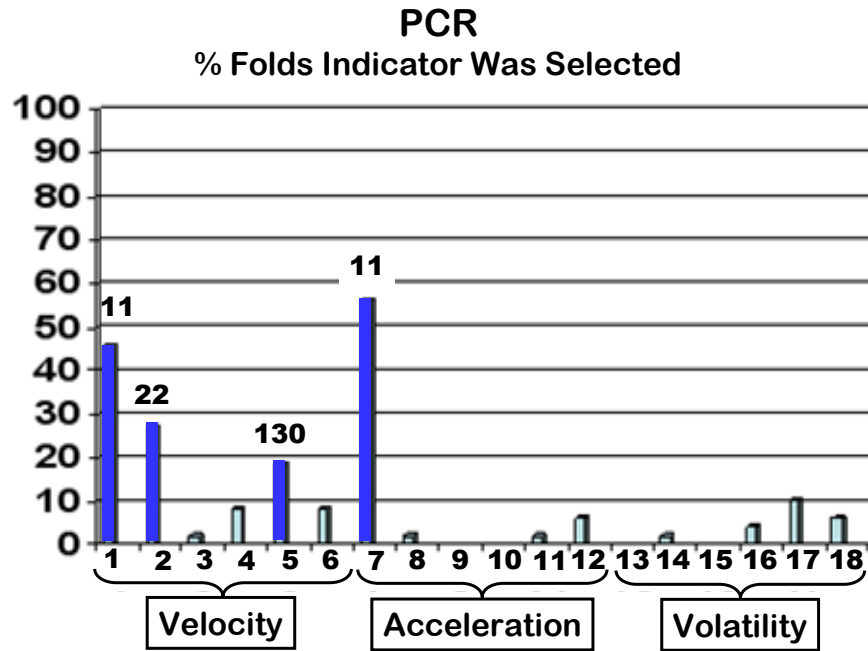


Fig. 7 18 Price Dynamics Indicators

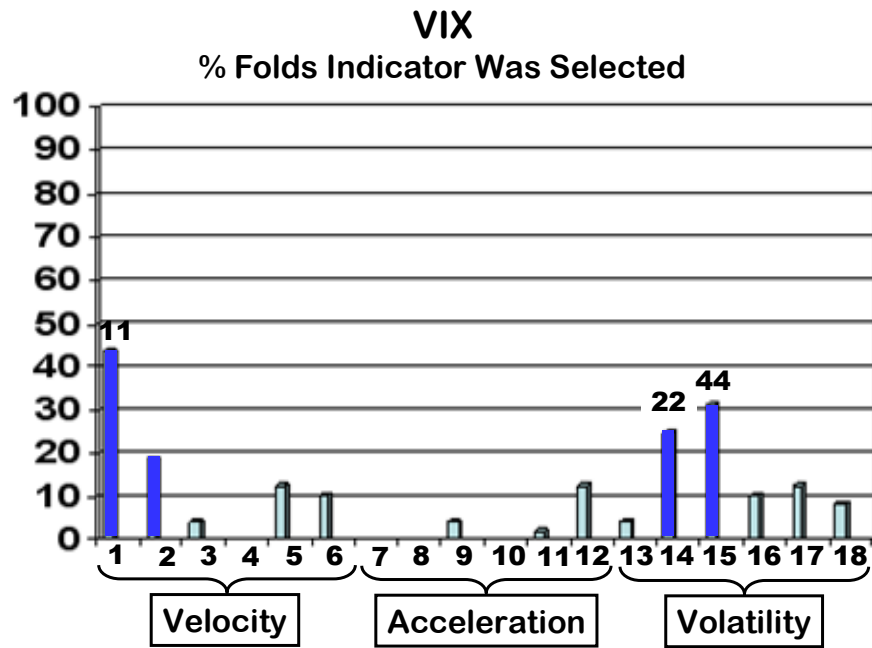


Fig. 8 18 Price Dynamics Indicators

C. Histories of SI & PSI

Figures 9 through 18 display the history of each SI and PSI exponentially smoothed to approximate a 65-day moving average (smoothing constant 0.0303). The SI series display considerable drift and change in variability. In contrast, the PSI display greater stability in both features, important attributes for signaling rules based on fixed thresholds.

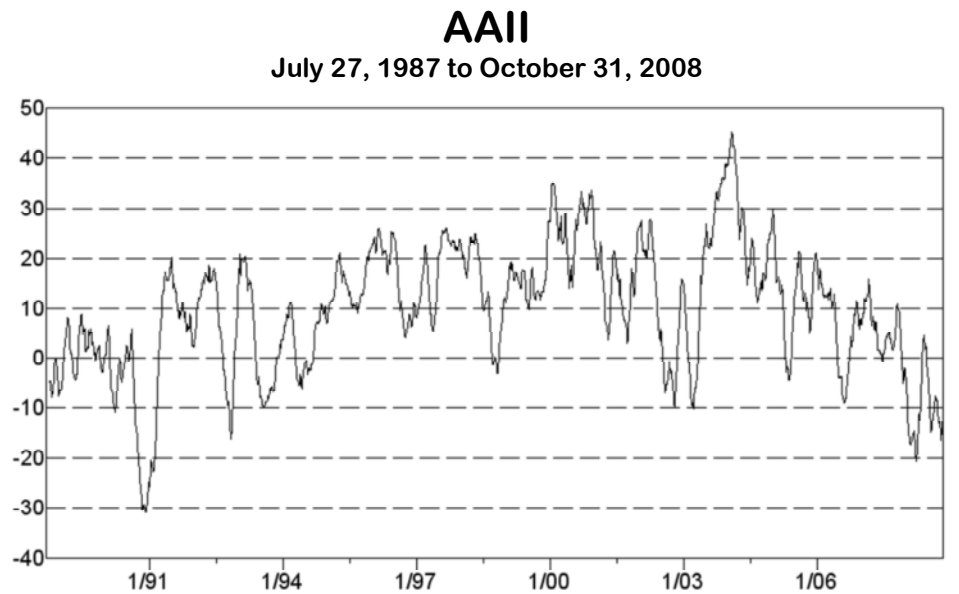


Fig. 9

AAll Purified

July 27, 1987 to October 31, 2008

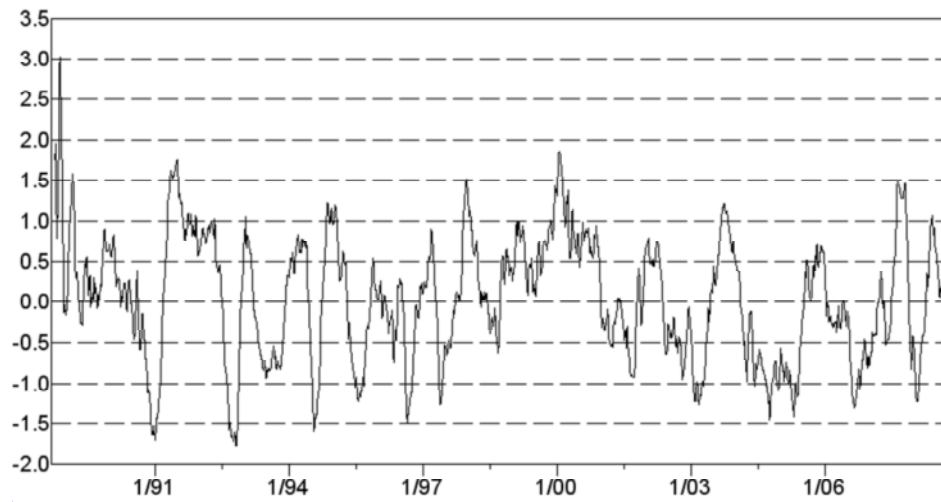


Fig. 10

HUL

January 2, 1985 to October 31, 2008

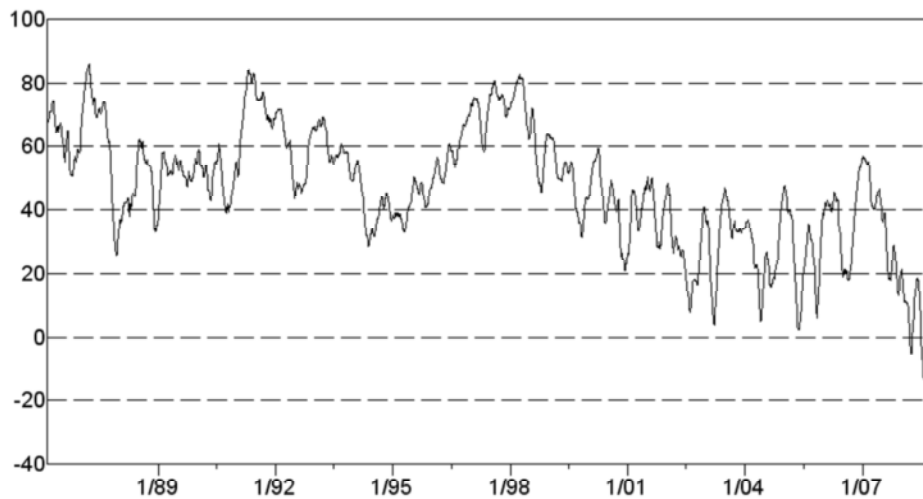


Fig. 11

HUL Purified

January 2, 1985 to October 31, 2008

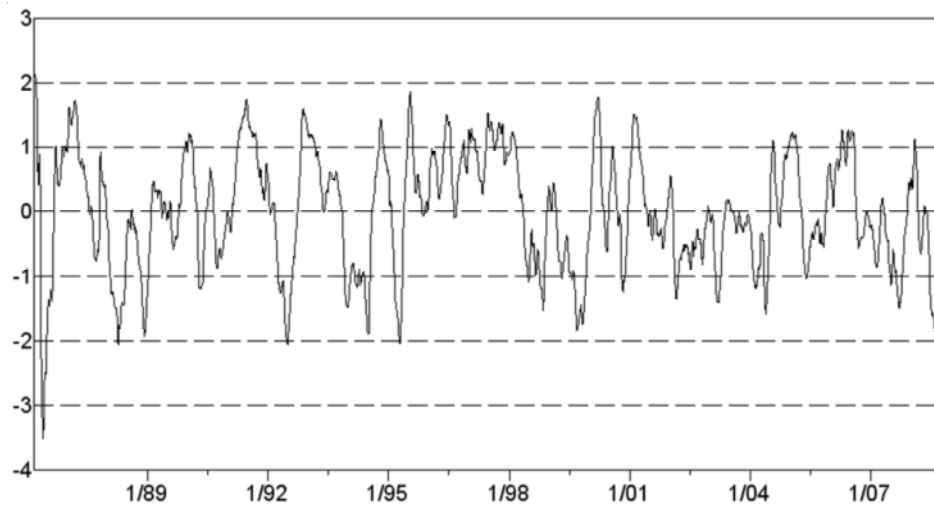


Fig. 12

INV

January 2, 1985 to October 31, 2008

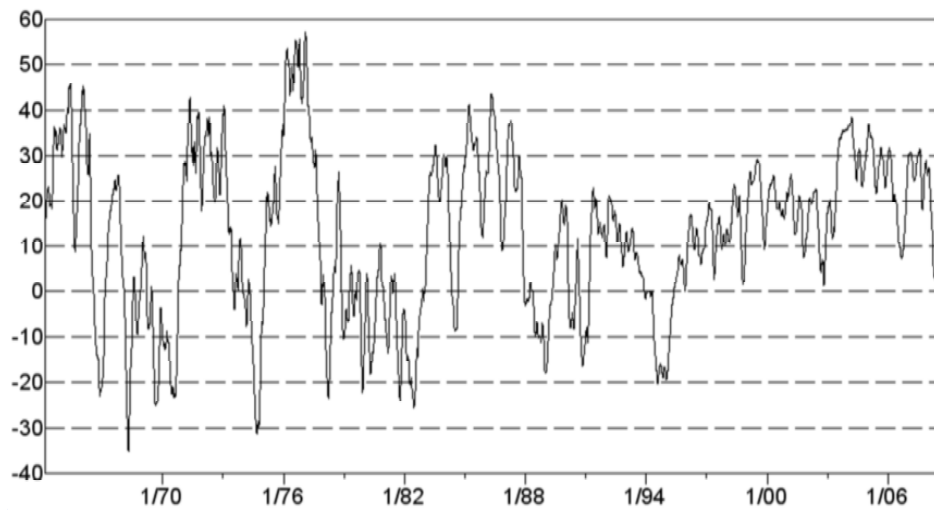


Fig. 13

INV Purified

January 2, 1985 to October 31, 2008

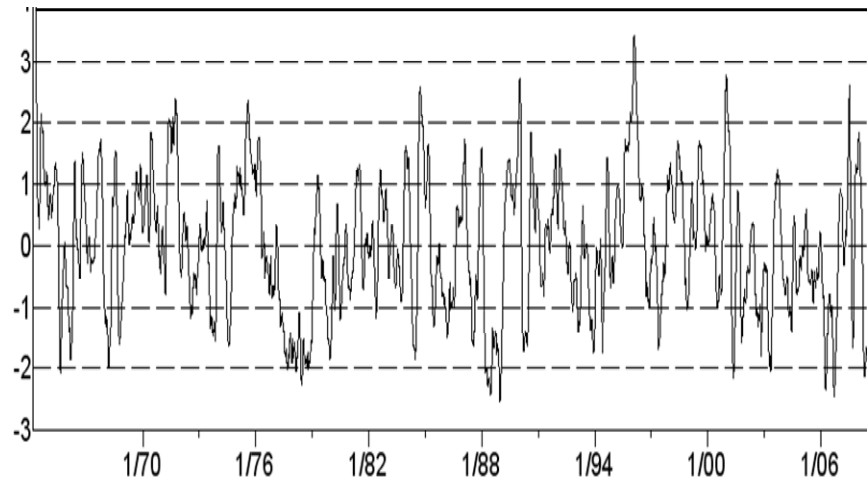


Fig. 14

PCR

December 9, 1986 to October 31, 2008

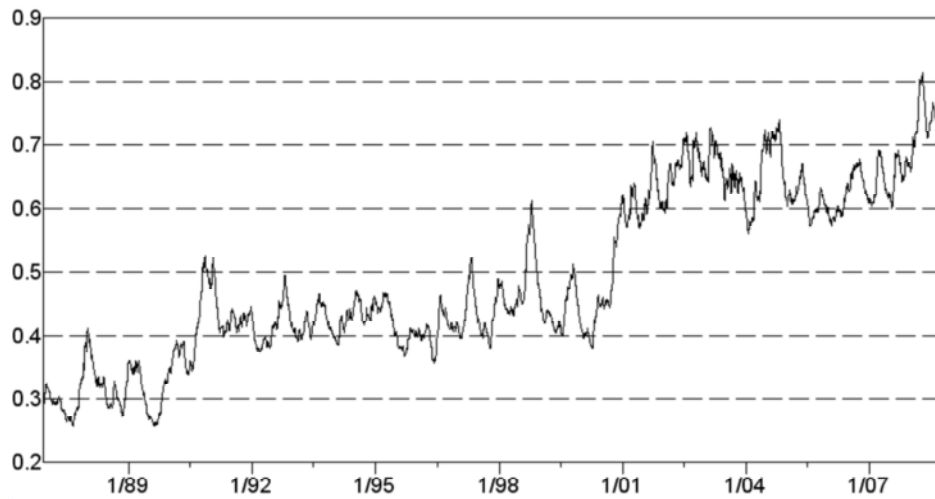


Fig. 15

PCR Purified

December 9, 1986 to October 31, 2008

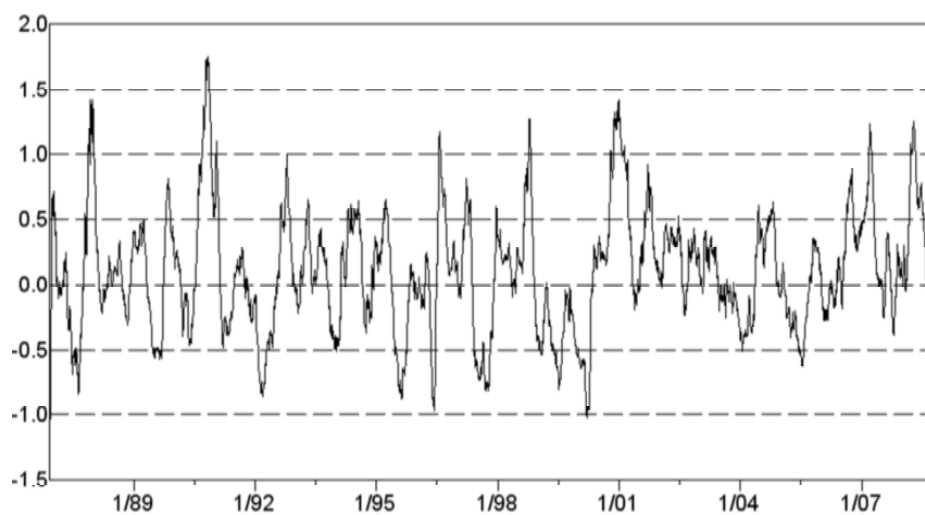


Fig. 16

VIX

March 11, 1987 to October 31, 2008

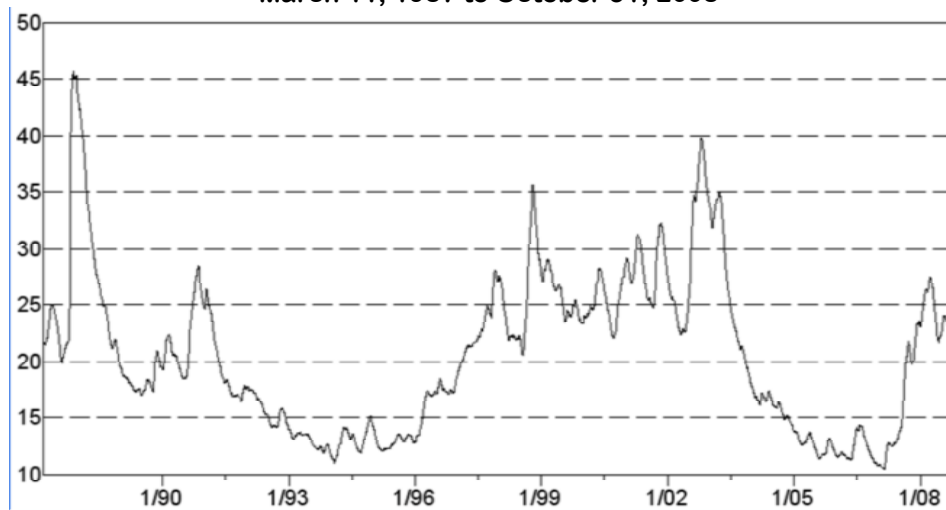


Fig. 17

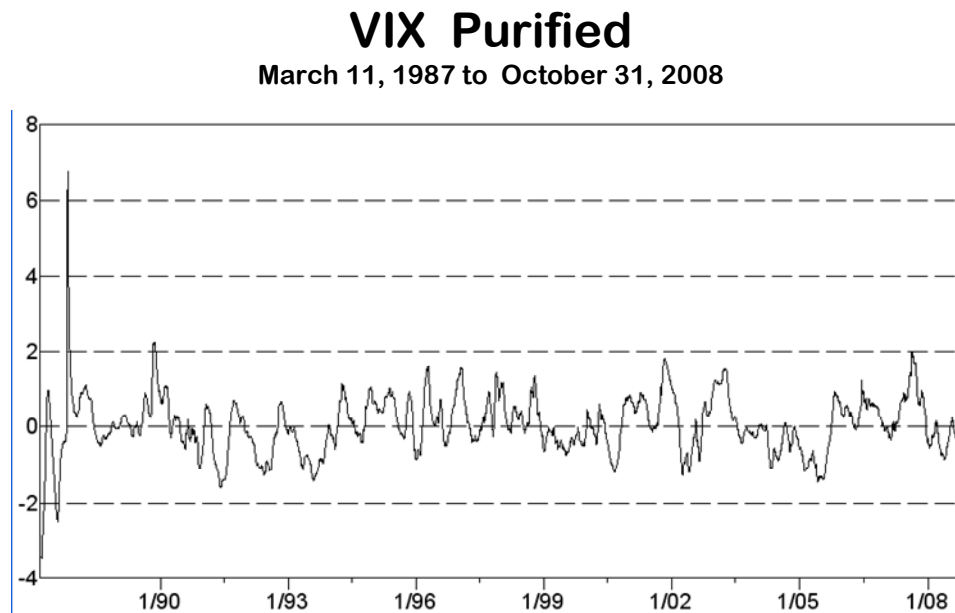


Fig. 18

D. Profit Factor Comparisons

Figures 19 through 28 show out-of-sample PF for 50 long and 50 short rules trading the S&P500 Index from January 1, 1990 through October 31, 2008. SI PF are depicted by red bars and PSI by blue. PF values are shown above each bar. Rules with statistically significant PF at the 0.05 level relative to a random signal taking the same number of positions are highlighted (asterisked and boxed). For comparison purposes Figures 29 through 34 show out-of-sample PF for 36 long and short rules based on 18 price dynamics indicators to indicate their predictive power for the SP500.

Profit Factors for Long Signals

AAII vs. **Purified AAI**

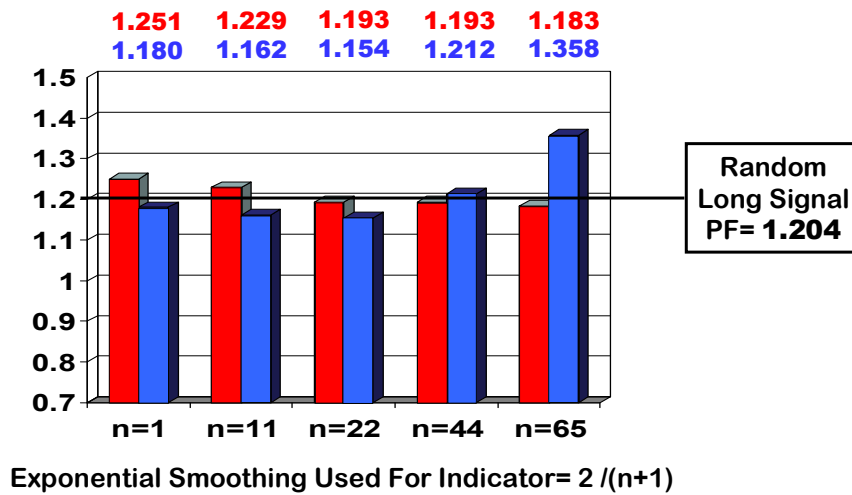


Fig. 19

Profit Factors for Short Signals

AAII vs. **Purified AAI**

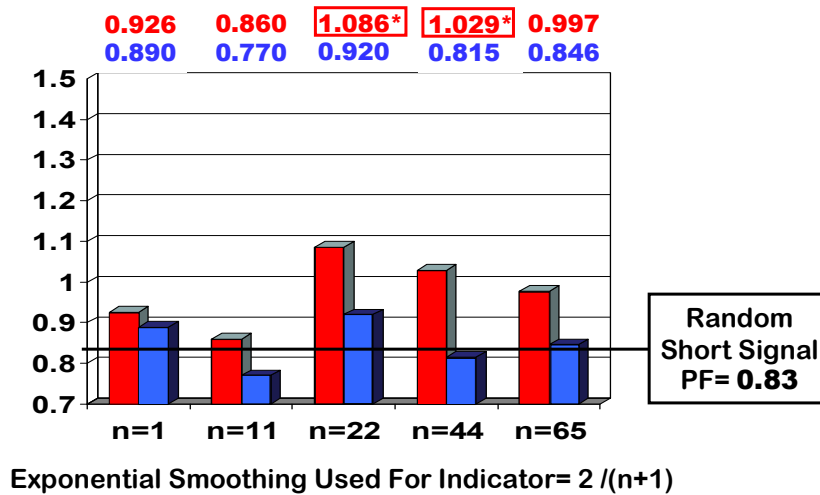


Fig. 20

Profit Factors for Long Signals HUL vs. Purified HUL

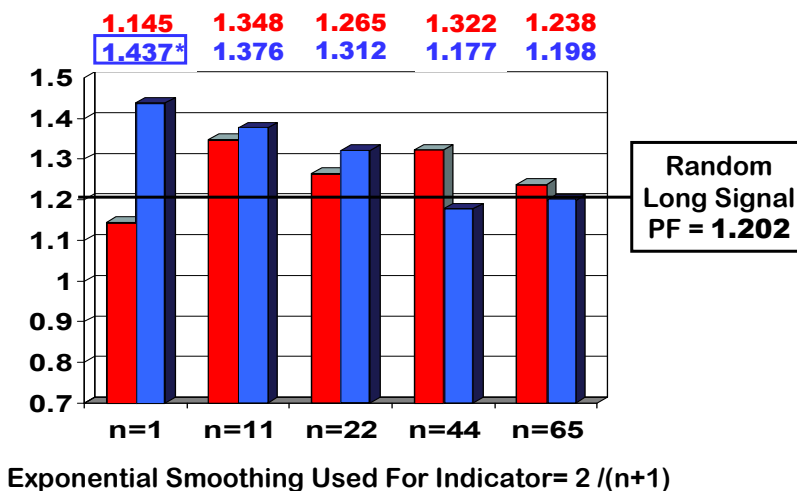


Fig. 21

Profit Factors for Short Signals HUL vs. Purified HUL

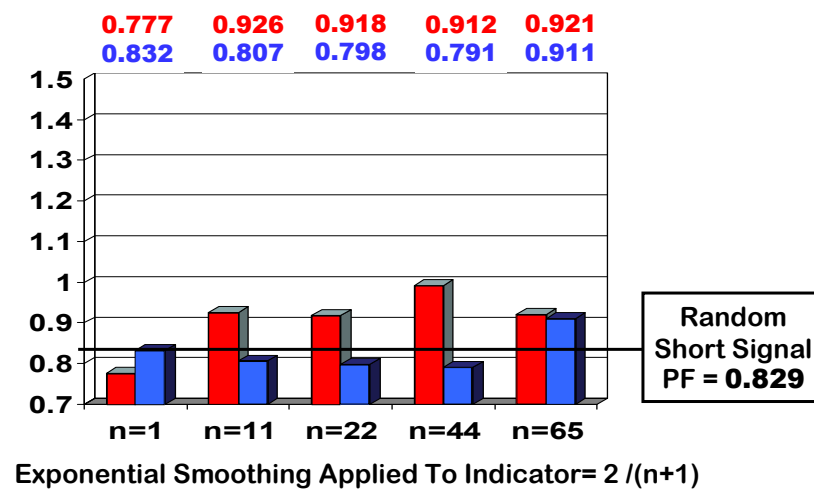


Fig. 22

Profit Factors for Long Signals

INV vs. **Purified INV**

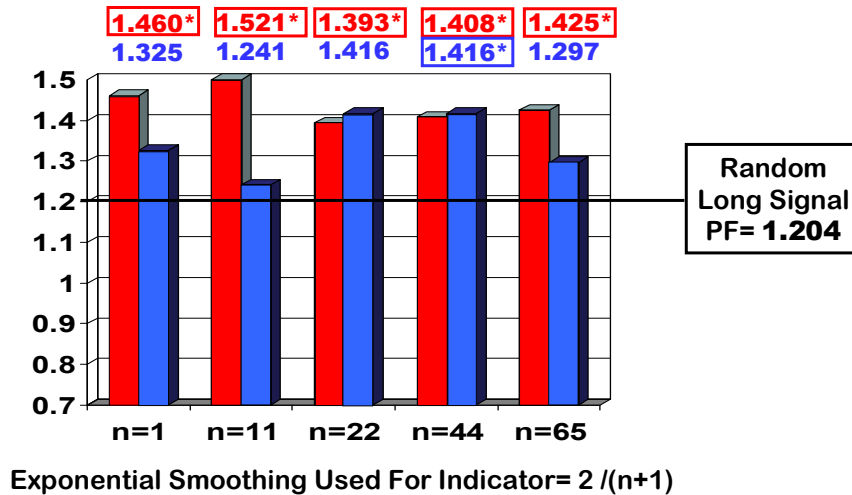


Fig. 23

Profit Factors for Short Signals

INV vs. **Purified INV**

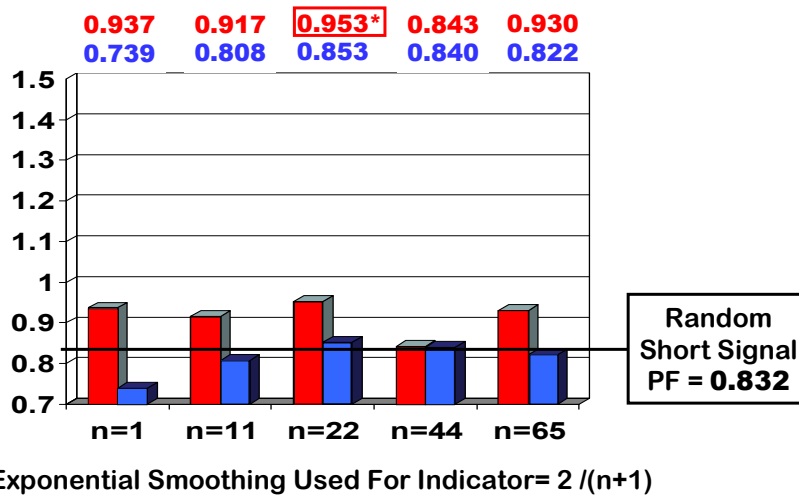
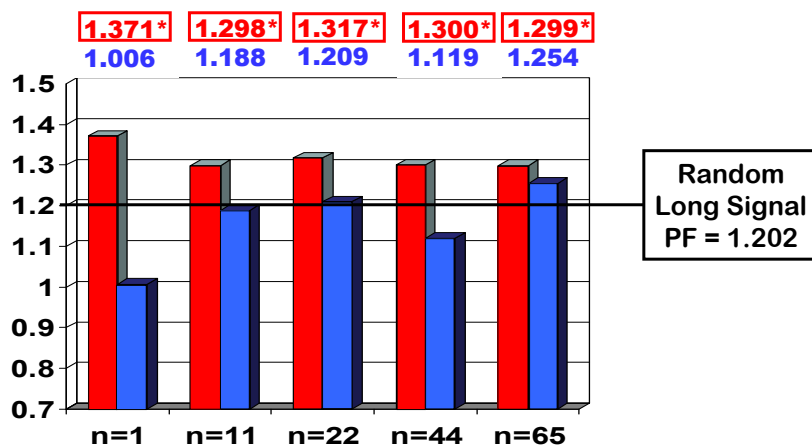


Fig. 24

Profit Factors for Long Signals

PCR vs. **Purified PCR**

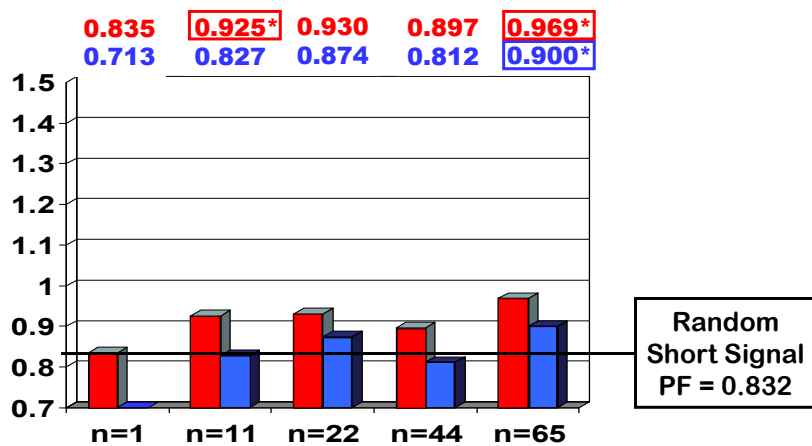


Exponential Smoothing Used For Indicator = $2/(n+1)$

Fig. 25

Profit Factors for Short Signals

PCR vs. **Purified PCR**



Exponential Smoothing Used For Indicator = $2/(n+1)$

Fig. 26

Profit Factors for Long Signals

VIX vs. Purified VIX

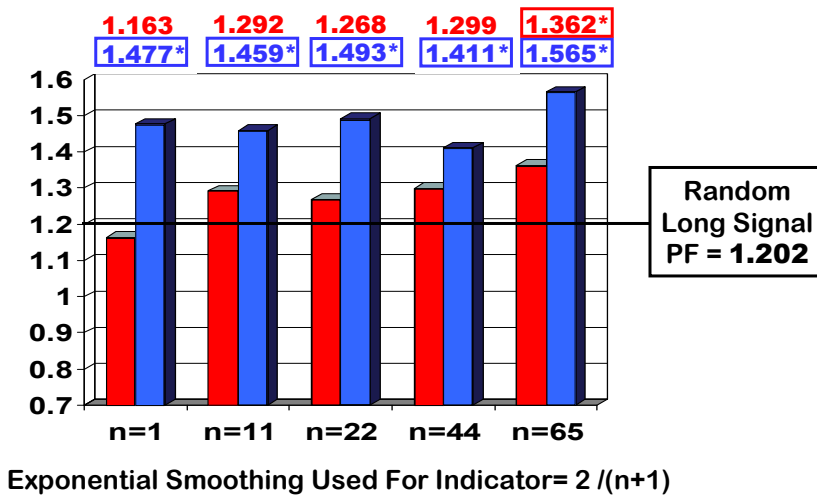


Fig. 27

Profit Factors for Short Signals

VIX vs. Purified VIX

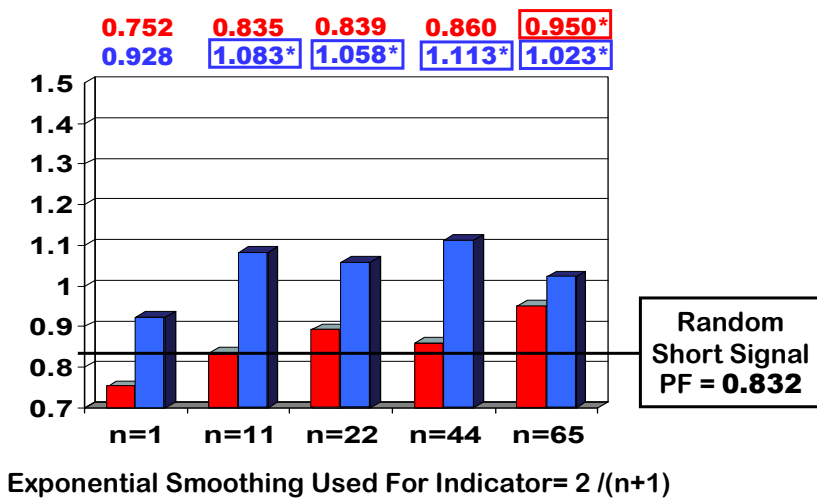


Fig. 28

Price Velocity Profit Factor: Long Signals

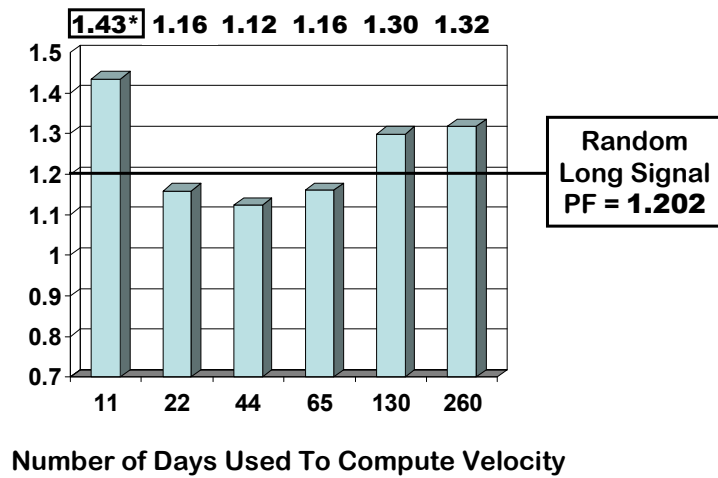


Fig. 29

Price Velocity Profit Factor: Short Signals

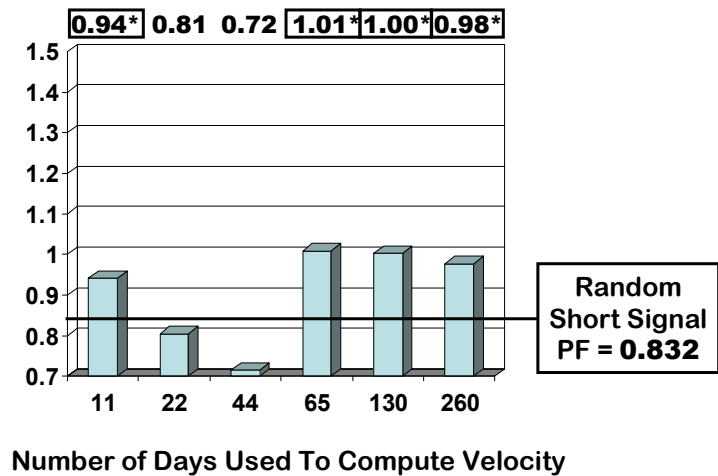


Fig. 30

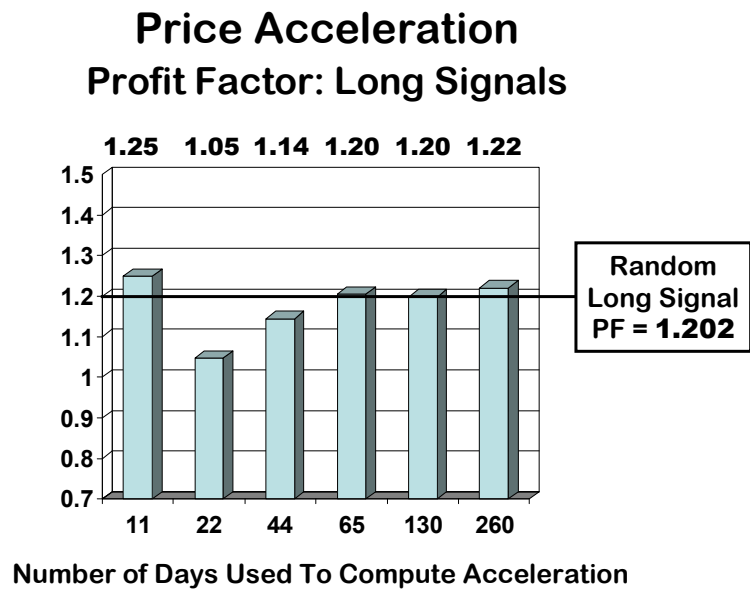


Fig. 31

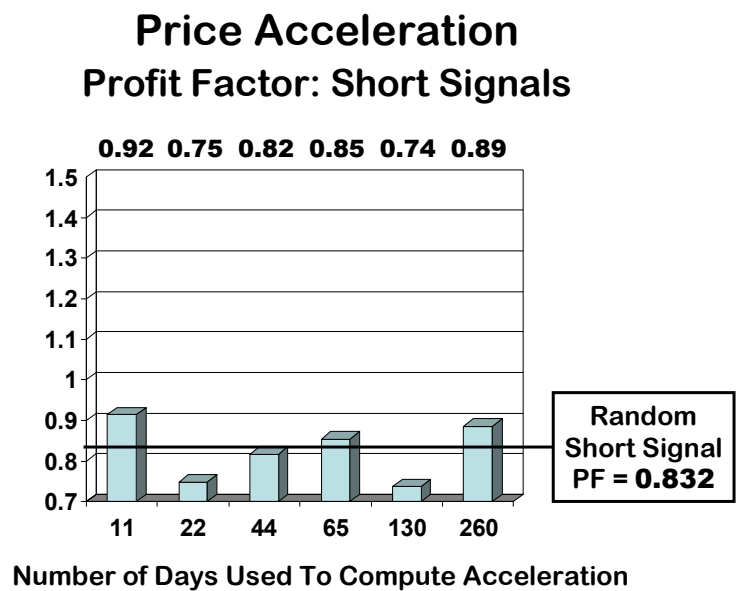


Fig. 32

Price Volatility Profit Factor: Long Signals

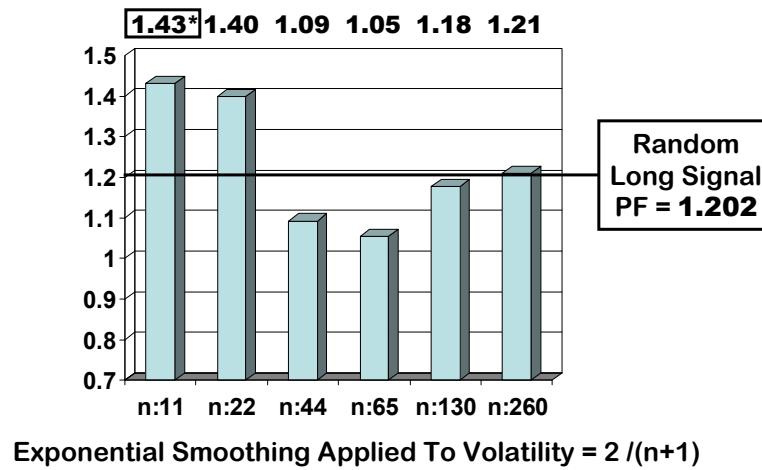


Fig. 33

Price Volatility Profit Factor: Long Signals

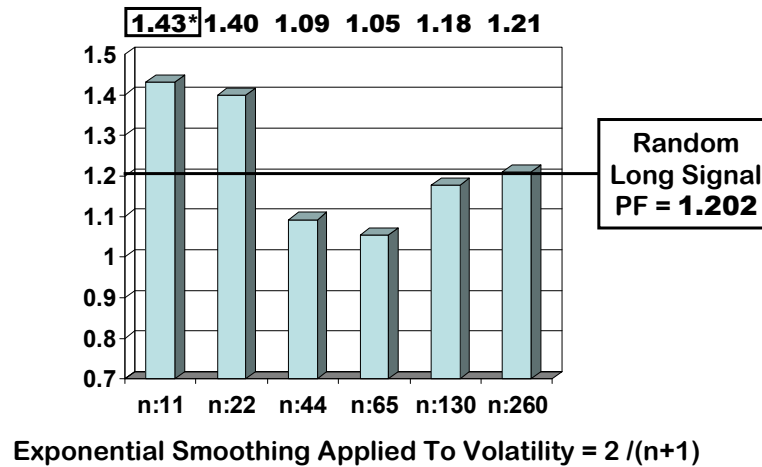


Fig. 33

Price Volatility Profit Factor: Short Signals

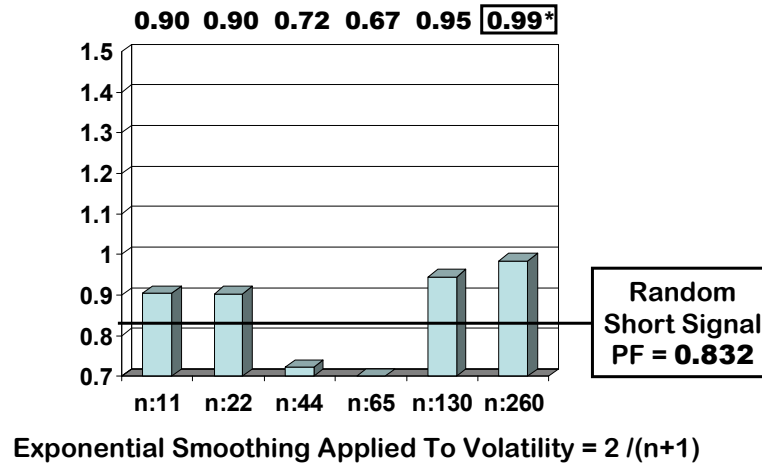


Fig. 34

IV. Discussion & Conclusion

The five SI series analyzed are generally well predicted from price dynamics. R-squared ranges from 0.27 to 0.70 with an average of 0.55, but these values are upwardly biased due to in-sample model fitting as well as selection bias in the choice of price dynamics indicators used as predictors. For this reason we show average r-squared values for all models tested in Figure 3b. However, there are differences as to which price dynamics indicators dominate for a given SI. Sentiment polls (INV, HUL and AAIL) are dominated by price velocity. PCR, the least well predicted, is dominated by 11-day acceleration. VIX is driven by velocity but also volatility (22 & 44 days). The relatively low r-squared for PCR may suggest a non-linear relationship to price dynamics, which our linear regression model would not pick up, other factors not included in our model, or a higher inherent unpredictability.

The obvious nonstationarity of SI seen in Figures 9, 11, 13, 15 and 17, which makes fixed-threshold signaling rules problematic, is markedly reduced by purification. The PSI in Figures 10, 12, 14, 16 and 17 speak

loudly to this point. Drift is eliminated and unstable variability is attenuated.

Our initial intuition that purification would improve predictive power for all SI was not substantiated. With respect to sentiment polls, AAIL, INV and HUL, 8 of 30 (long & short) rules based on unpurified SI (red bars in Figures 19 through 24) were significant at the 0.05 level. Only 2 of 30 rules based on PSI (blue bars in Figures 19 through 24) were significant. The one instance where PSI was significant and superior to the SI version (long rule for HUL $n=1$ in Figure 21) seems too isolated to be important.

Rules based on unpurified PCR (red bars in Figures 25 and 26) yielded a significant PF in 7 of 10 cases. Only 1 of 10 rules based on purified PCR produced a significant PF, and in all instances PF based on the PSI version of PCR were lower than SI versions. The strong drift in PCR (Figure 15) calls into question the 7 significant PF, as the rules were based on fixed thresholds.

The standout exception is VIX. Figures 27 and 28 show purification produces a strong improvement PF. While only 2 of 10 rules based on unpurified VIX beat a random signal, 9 of 10 rules based on purified VIX display a significant PF. This suggests that VIX contains predictive information above and beyond price dynamics that is masked by the strong influence that price dynamics have on VIX. *We believe that purified VIX represents an improvement over standard VIX, and price dynamics purification represents a step forward in sentiment analysis in general as it can point to indicators that contain information that is not redundant of that found in price indicators.* We are at a loss, however, to explain why VIX contains information beyond price or why price clouds that information. This is a worthwhile area of inquiry as it may point to new areas of sentiment analysis.

Of the 36 long & short rules based on the 18 price dynamics indicators (Figures 29 through 34), 7 produced profit factors that are statistically significant relative to a random signal. Of these, 5 are velocity based and 2 are volatility based. Acceleration produced no significant rules. The

predictive power in velocity and the strong impact of velocity on sentiment polls (AAII, INV & HUL) suggests that the predictive power residing in the unpurified form may largely derive from the predictive power of velocity. In other words, the polls are proxies for price velocity.

A strong motivation for utilizing SI is to obtain predictive information that is independent of and accretive to that found in price-based indicators. Our study suggests that AAI, INV, HUL and PCR add minimal value once price indicators have been utilized. This is most problematic for analysts who use subjective judgment to combine price indicators with unpurified sentiment indicators. This double counting could result in price being given excessive weight. Those using a statistical model derived with automated indicator selection do not face this issue as redundant indicators are not likely to be included in the model.

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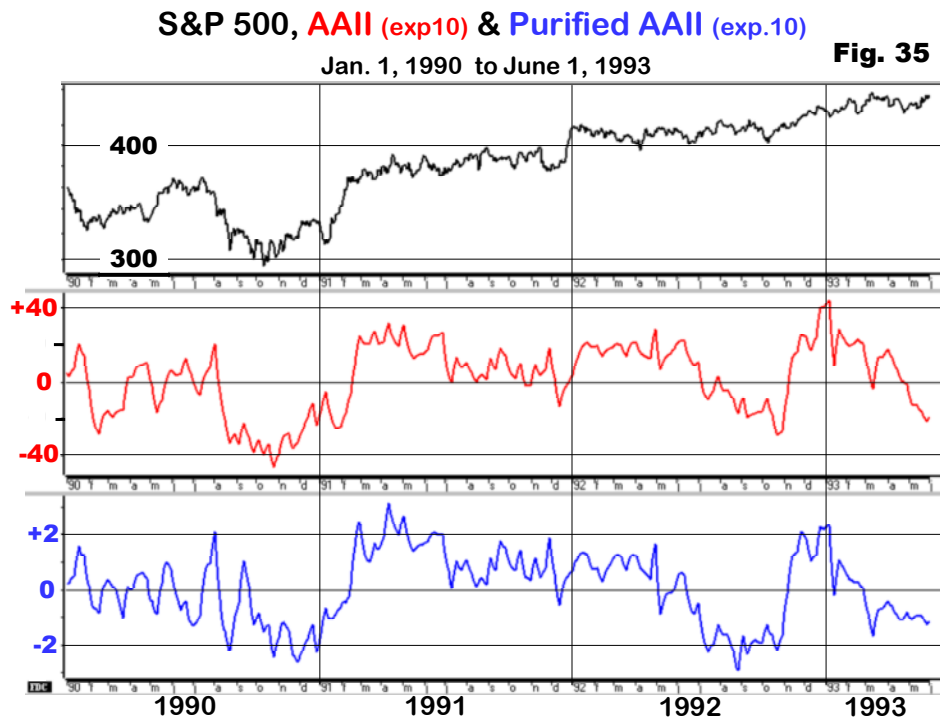
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Appendix 1

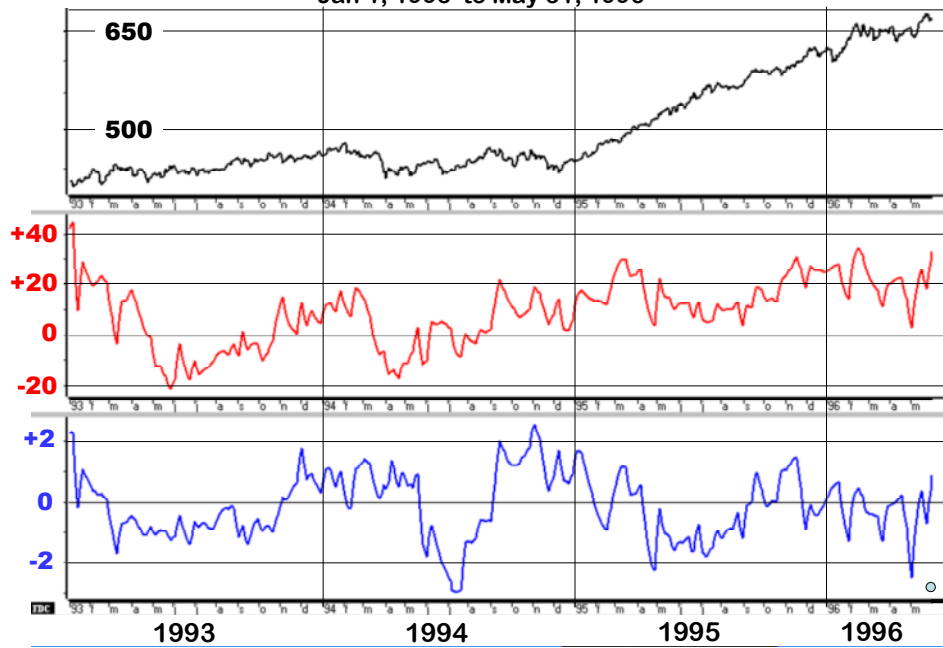
Figures 35 through 63 provide more detailed views of SI (red), PSI (blue) and the SP500. The indicators displayed are the 10 day exponentially smoothed version of each SI and PSI.



S&P 500, **AAll (exp10)** & **Purified AAll (exp10)**

Jan 1, 1993 to May 31, 1996

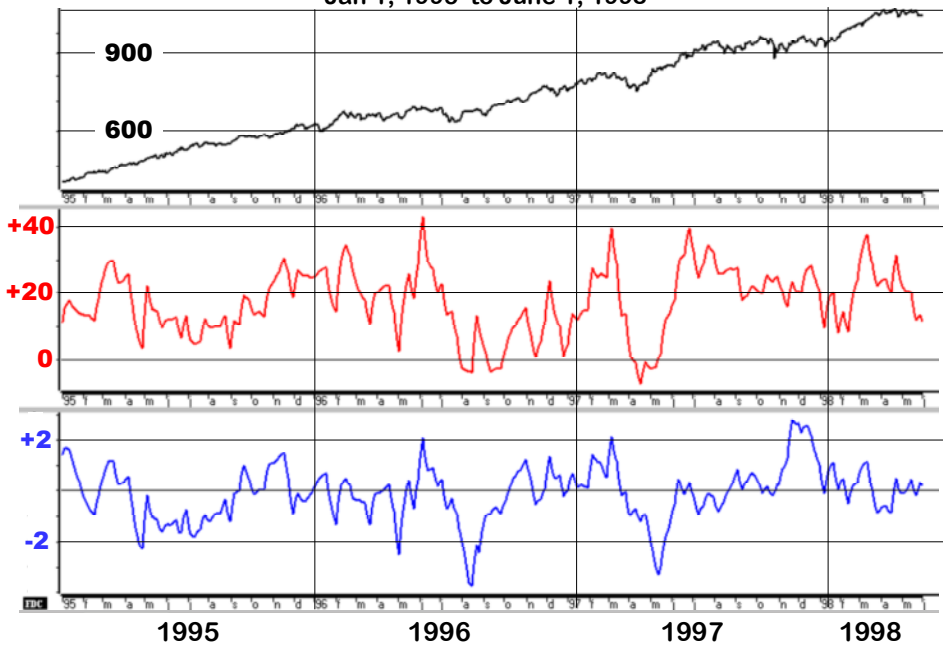
Fig. 36



S&P 500, **AAll (expo.10)** & **Purified AAll (exp10)**

Jan 1, 1995 to June 1, 1998

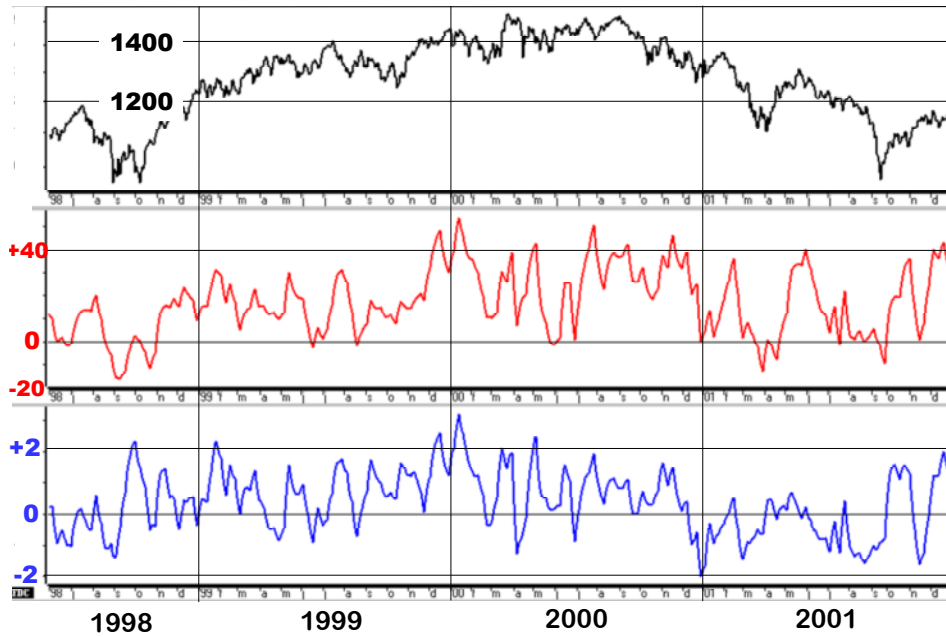
Fig. 37



S&P 500, **AII** (exp10) & **Purified AII** (exp10)

June 1, 1998 to Jan 1, 2002

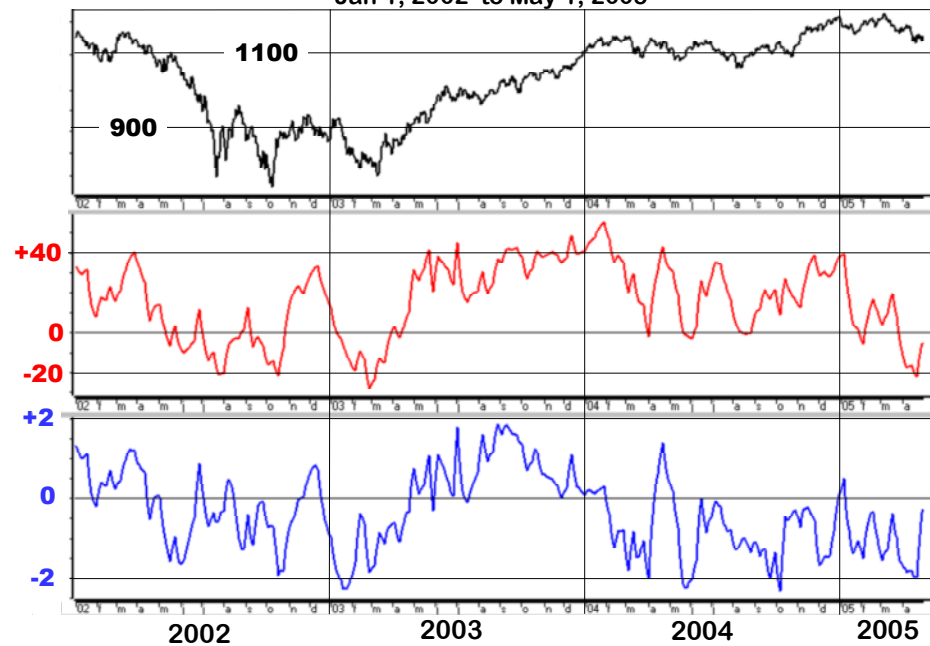
Fig. 38



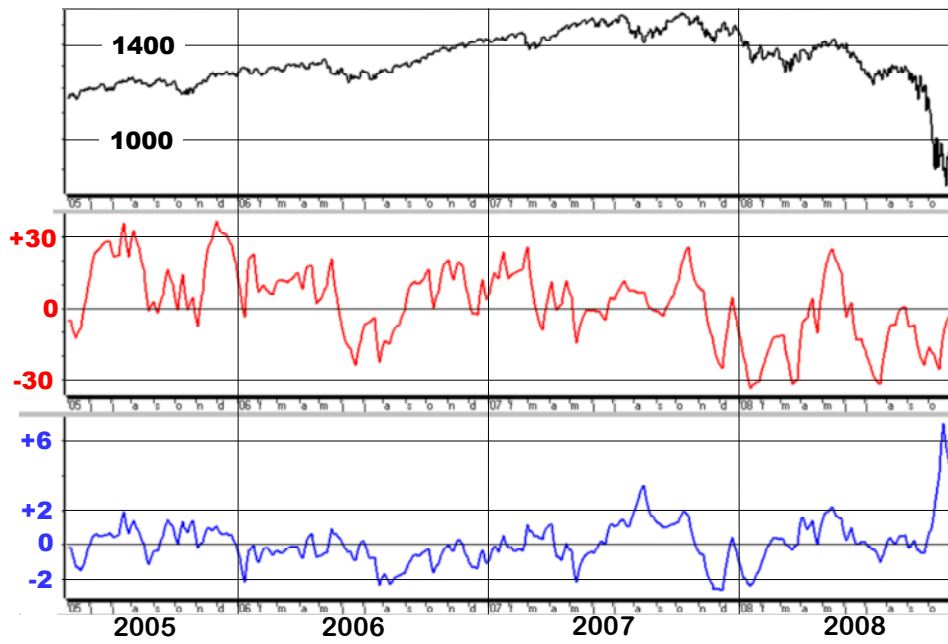
S&P 500, **AII** (exp10) & **Purified AII** (exp10)

Jan 1, 2002 to May 1, 2005

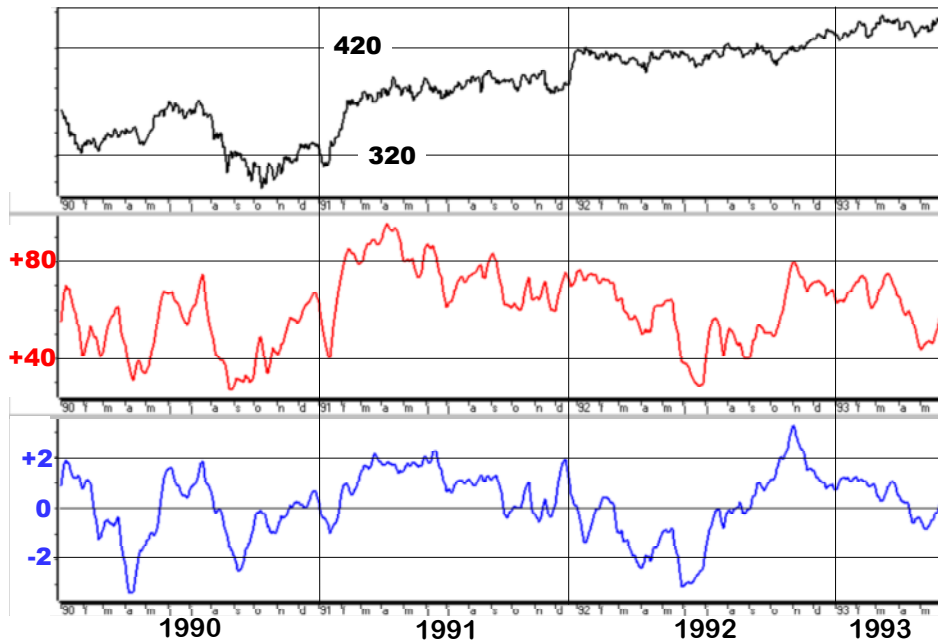
Fig. 39



S&P 500, AII (exp10) & Purified AII (exp10)
 May 1, 2005 to Oct 31, 2008 **Fig. 40**



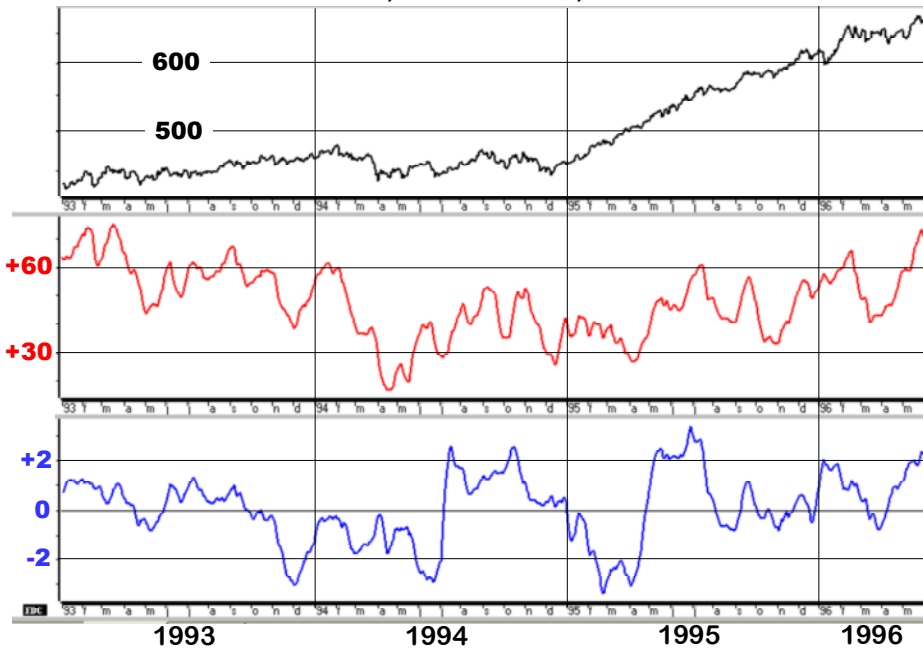
S&P 500, HUL (exp10) & Purified HUL (exp10)
 Jan. 1, 1990 to Sept 1, 1993 **Fig. 41**



S&P 500, **HUL (exp10)** & **Purified HUL (exp10)**

Jan. 1, 1993 to June 1, 1996

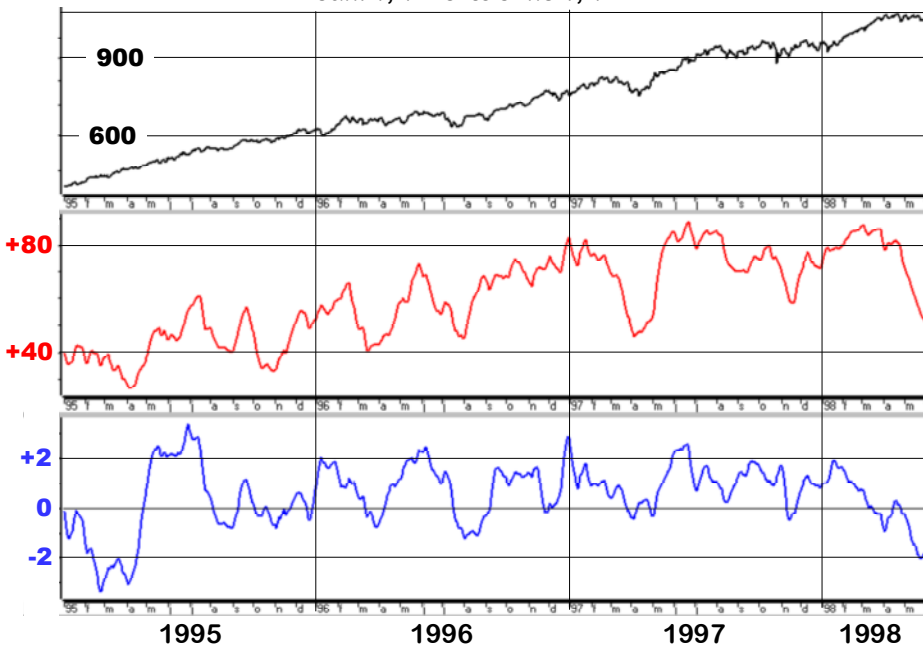
Fig. 42



S&P 500, **HUL (exp10)** & **Purified HUL (exp10)**

Jan. 1, 1995 to June 1, 1998

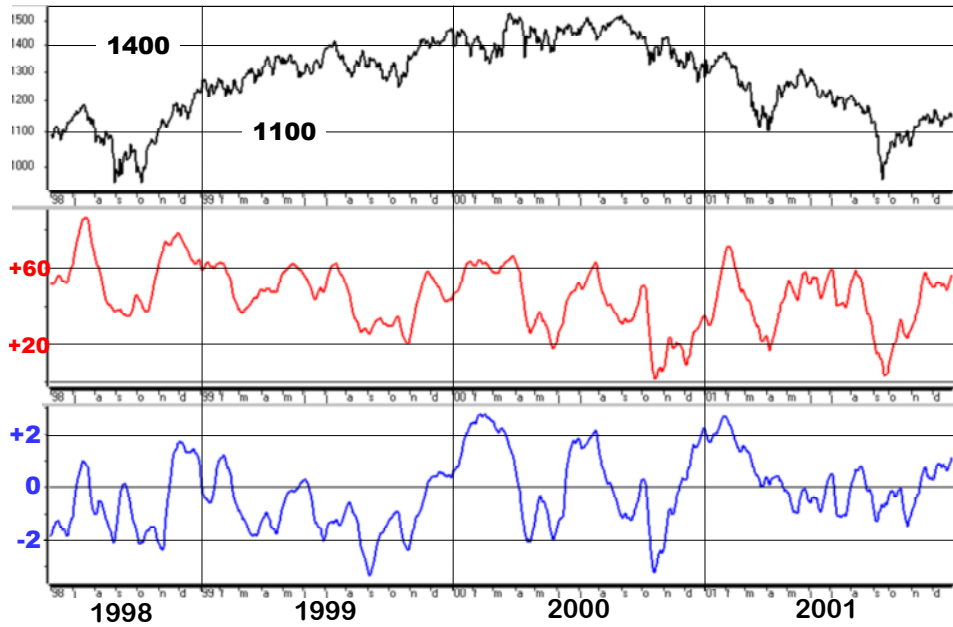
Fig. 43



S&P 500, **HUL (exp10)** & **Purified HUL (exp10)**

June 1, 1998 to Jan. 1, 2002

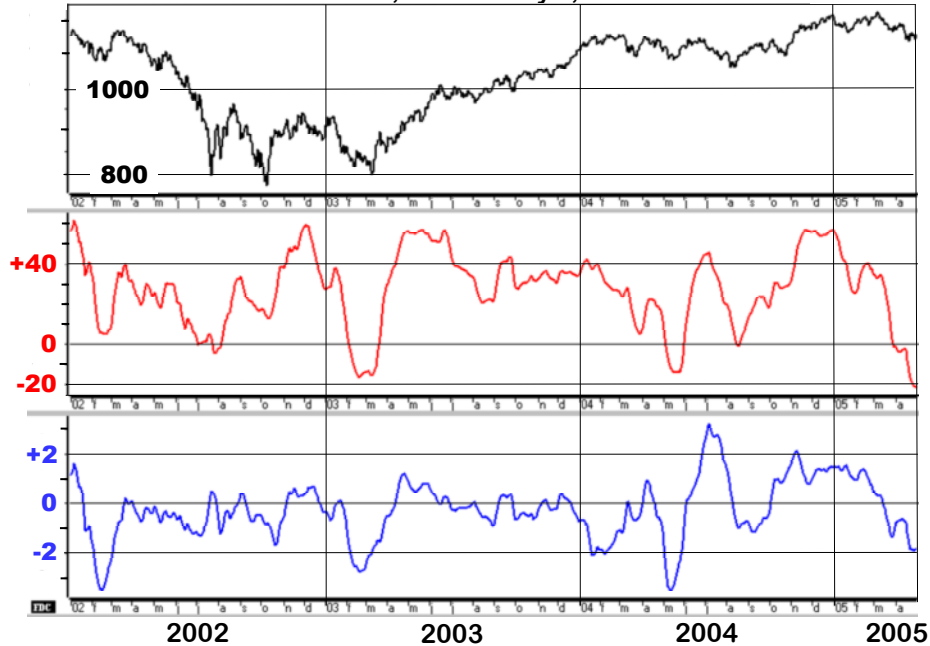
Fig. 44



S&P 500, **HUL (exp10)** & **Purified HUL (exp10)**

Jan 1, 2002 to May 1, 2005

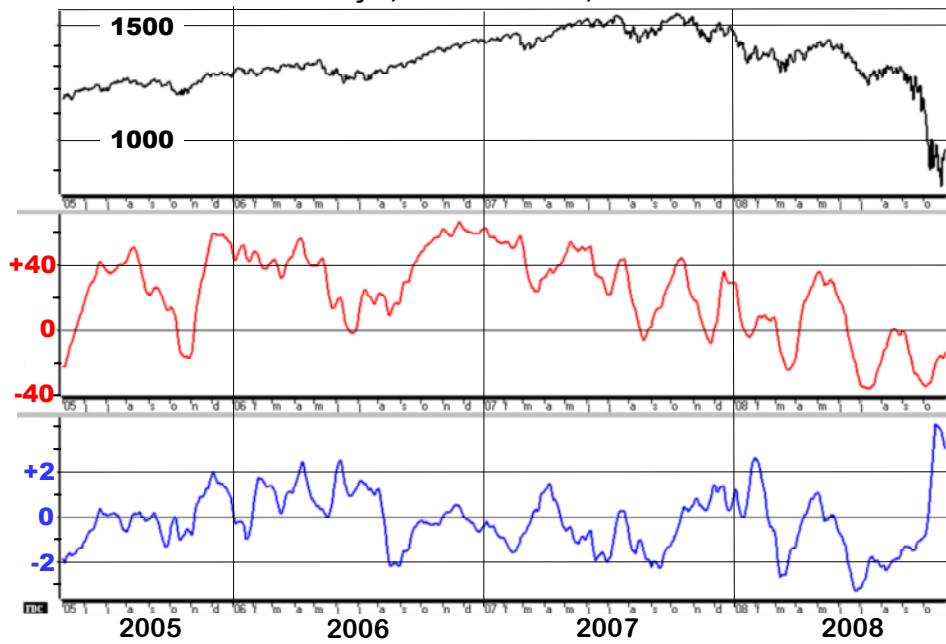
Fig. 45



S&P 500, HUL (exp10) & Purified HUL (exp10)

May 3, 2005 to Oct. 31, 2008

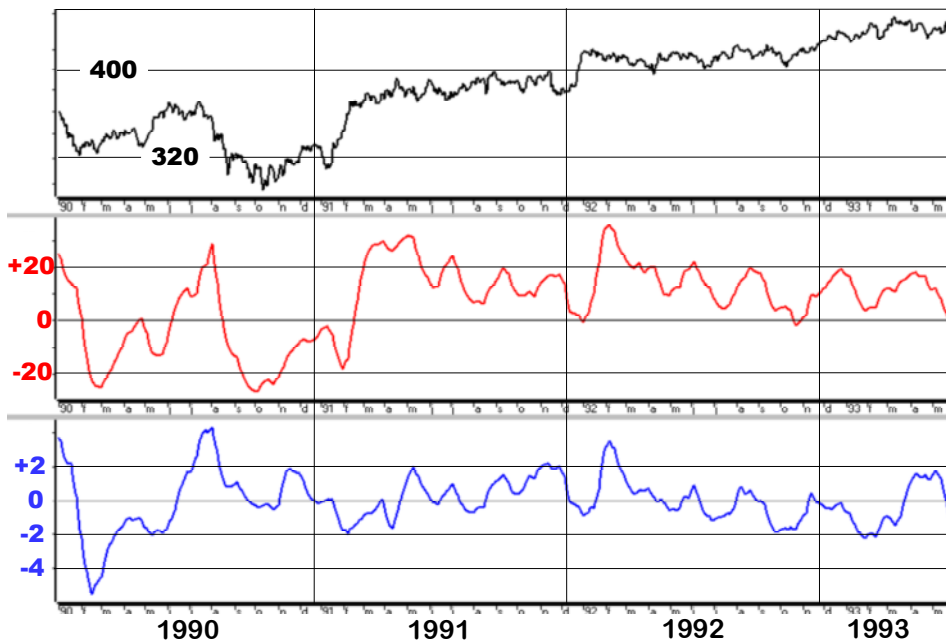
Fig. 46



S&P 500, INV (exp10) & Purified INV (exp10)

Jan. 1, 1990 to Sept 1, 1993

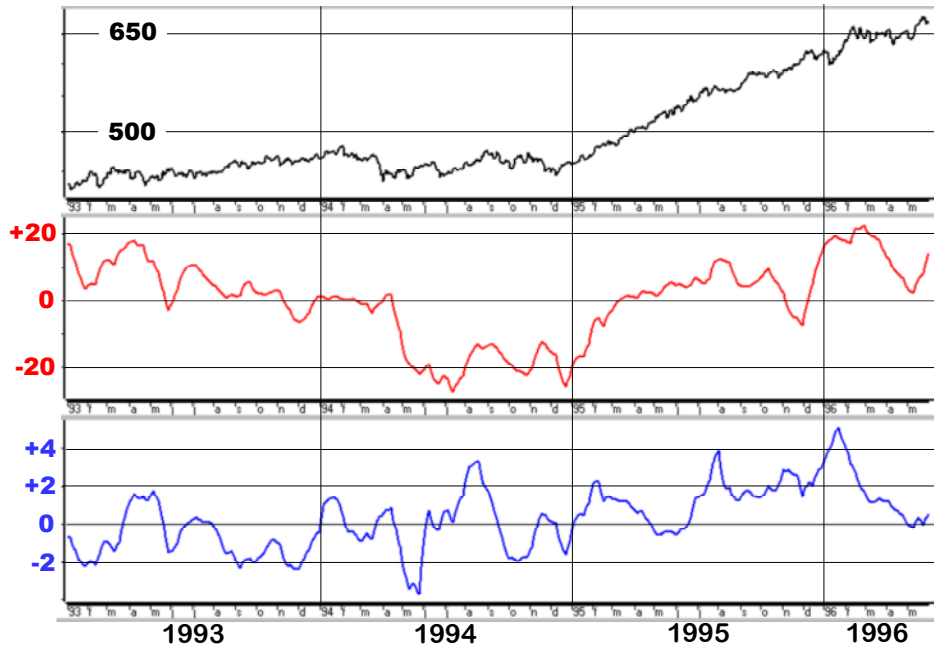
Fig. 47



S&P 500, INV (exp10) & Purified INV (exp10)

Jan. 1, 1993 to June 1, 1996

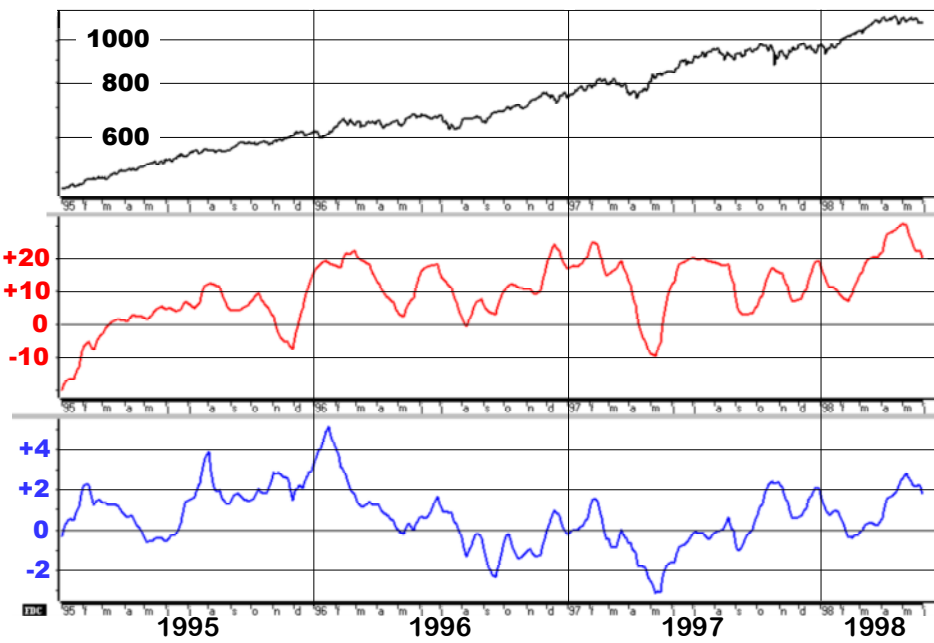
Fig. 48



S&P 500, INV (exp10) & Purified INV (exp10)

Jan. 1, 1995 to June 1, 1998

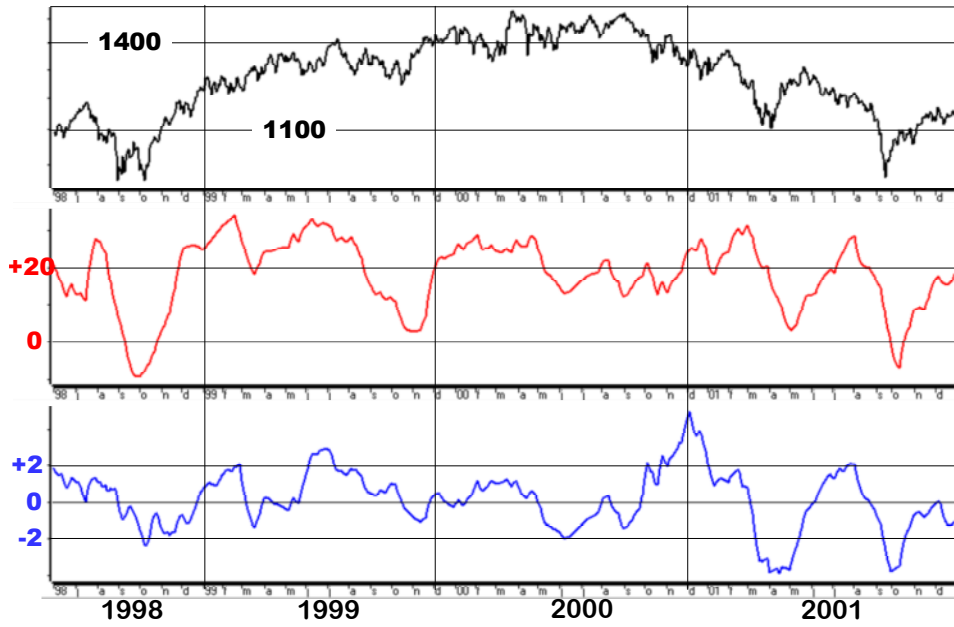
Fig. 49



S&P 500, **INV** (exp10) & **Purified INV** (exp10)

June 1, 1998 to Jan. 1, 2002

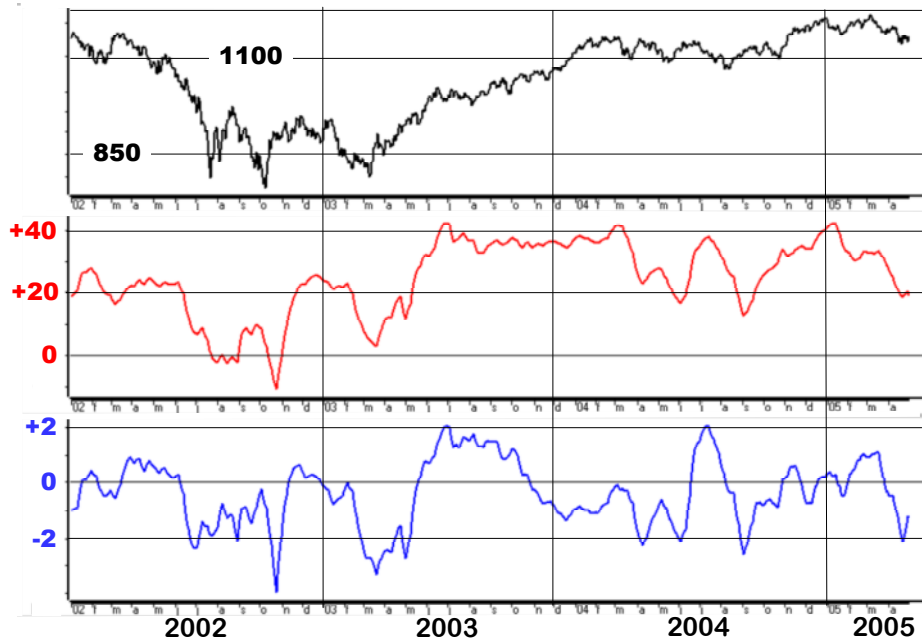
Fig. 49



S&P 500, **INV** (exp10) & **Purified INV** (exp10)

Jan 1, 2002 to May 1, 2005

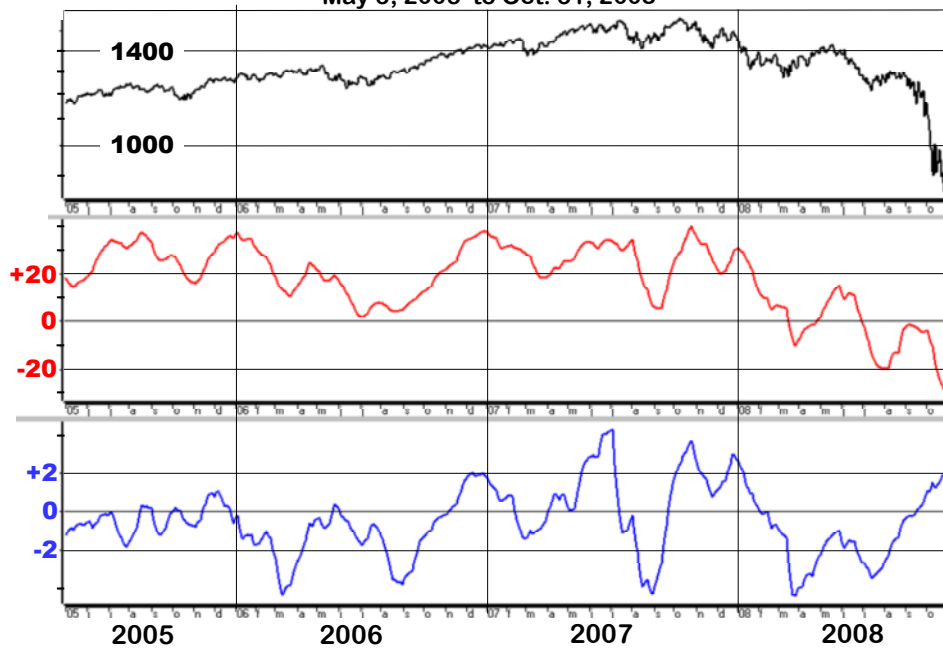
Fig. 50



S&P 500, INV (exp10) & Purified INV (exp10)

May 3, 2005 to Oct. 31, 2008

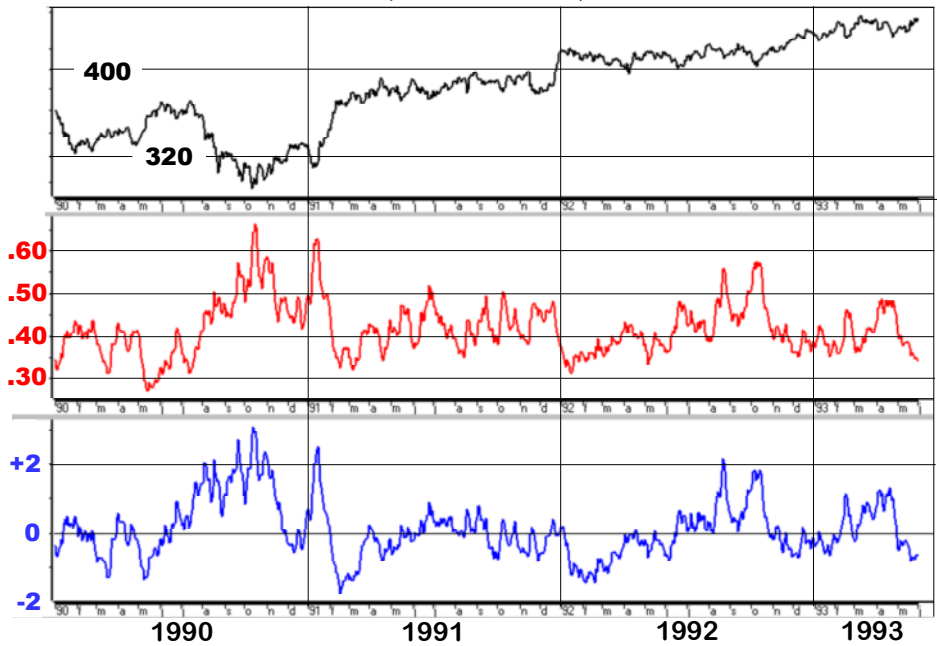
Fig. 51



S&P 500, PCR (exp10) & Purified PCR (exp10)

Jan. 1, 1990 to June 1, 1993

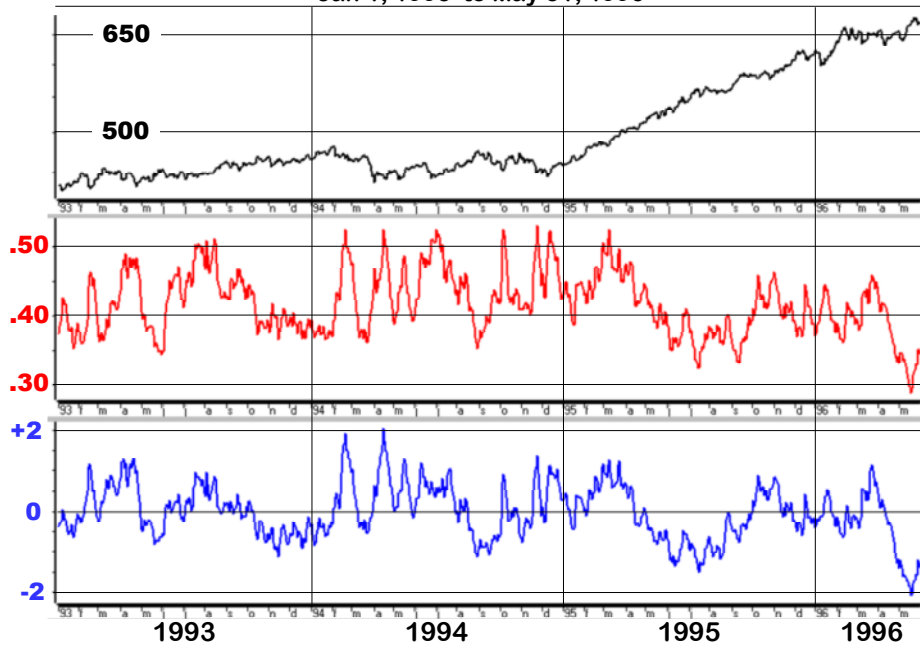
Fig. 52



S&P 500, **PCR** (exp10) & **Purified PCR** (exp10)

Jan 1, 1993 to May 31, 1996

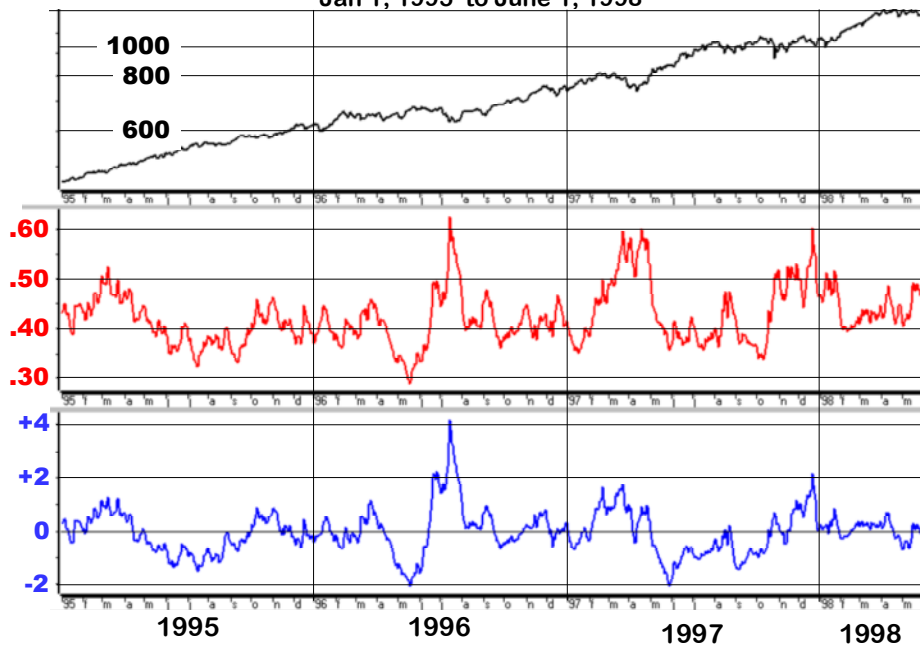
Fig. 53



S&P 500, **PCR** (exp10) & **Purified PCR** (exp10)

Jan 1, 1995 to June 1, 1998

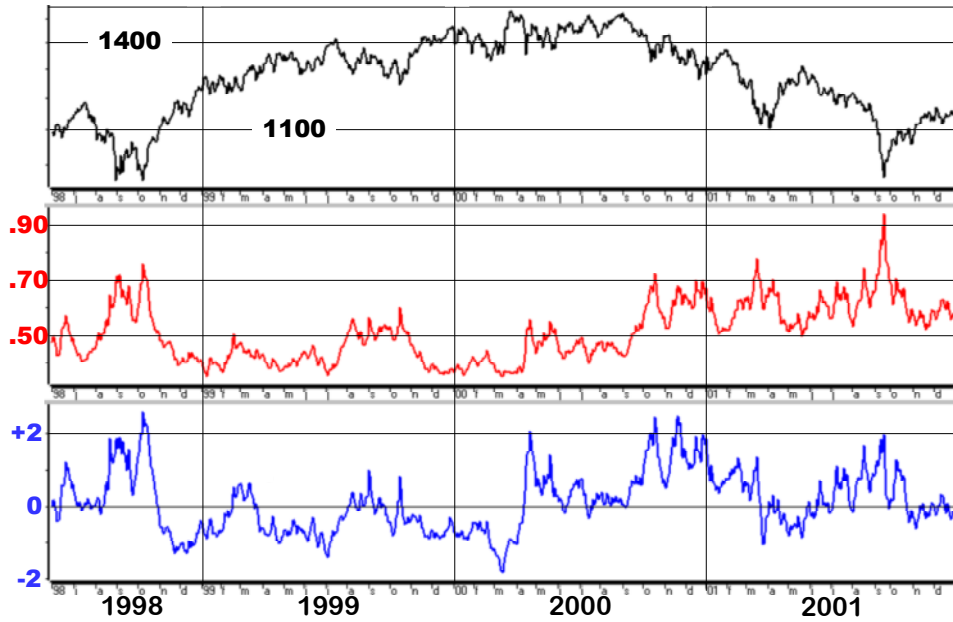
Fig. 54



S&P 500, PCR (exp10) & Purified PCR (exp10)

June 1, 1998 to Jan 1, 2002

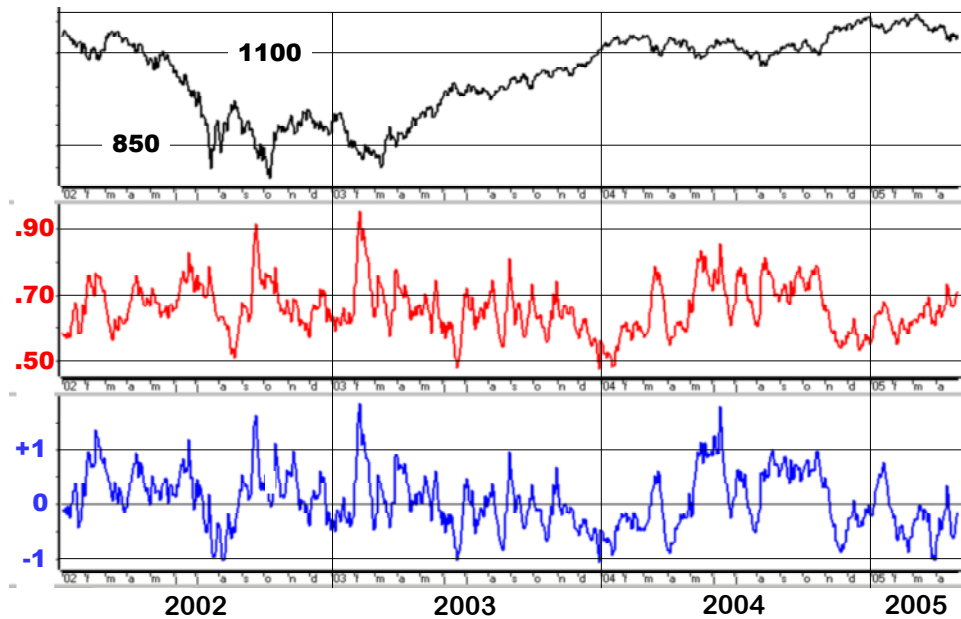
Fig. 55



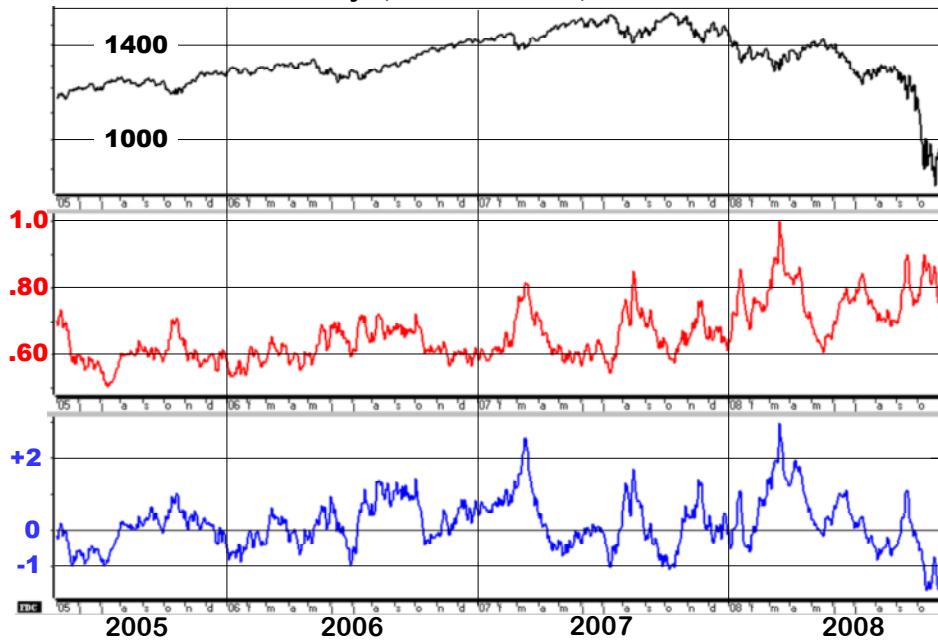
S&P 500, PCR (exp10) & Purified PCR (exp10)

Jan 1, 2002 to May 1, 2005

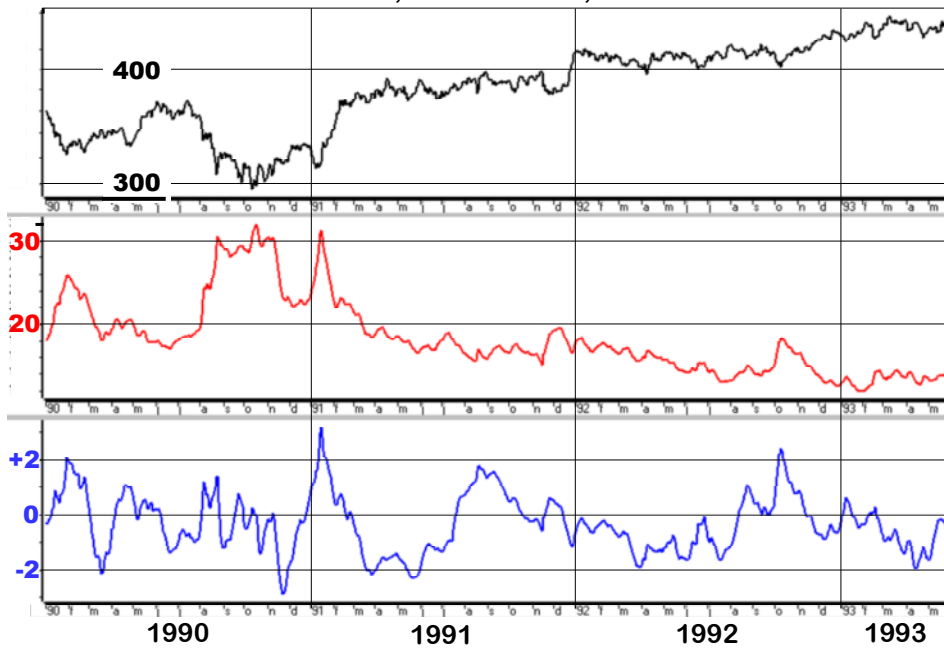
Fig. 56



S&P 500, PCR (exp10) & Purified PCR (exp10)
 May 1, 2005 to Oct. 31, 2008 **Fig. 57**



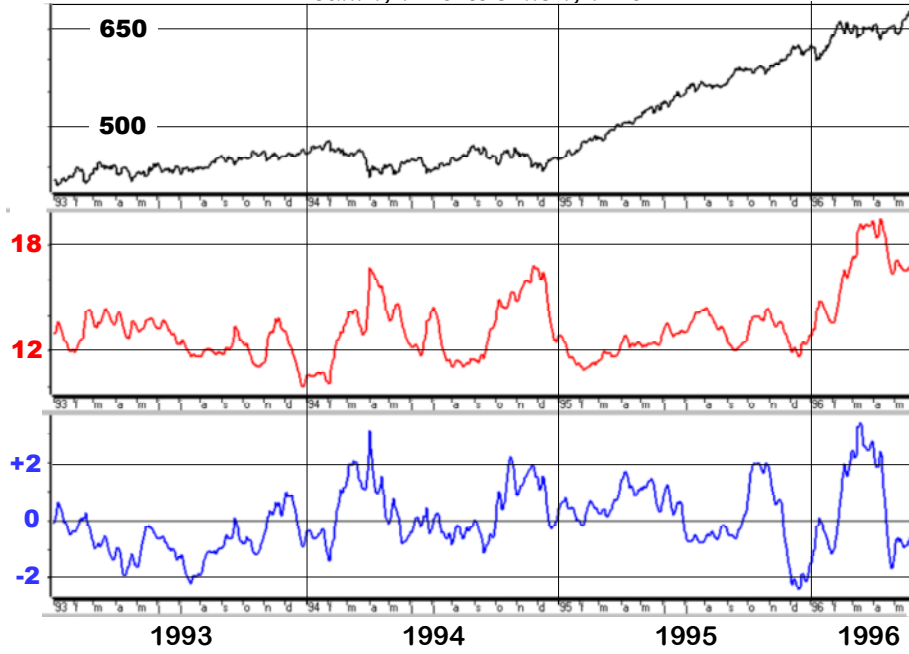
S&P 500, VIX (exp10) & Purified VIX (exp10)
 Jan. 1, 1990 to June 1, 1993 **Fig. 58**



S&P 500, **VIX** (exp10) & **Purified VIX** (exp10)

Jan. 1, 1993 to June 1, 1996

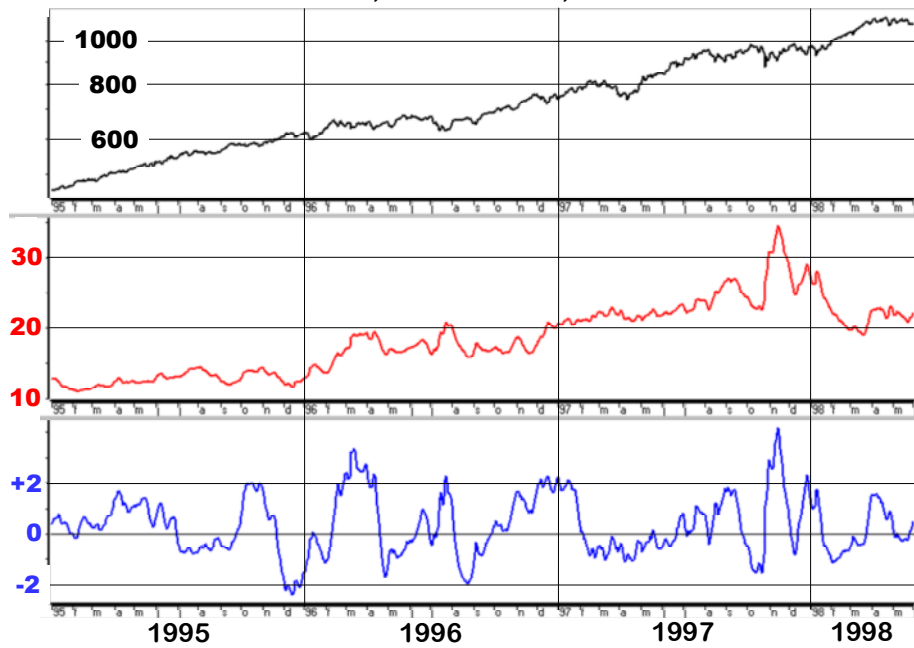
Fig. 59



S&P 500, **VIX** (exp10) & **Purified VIX** (exp10)

Jan. 1, 1995 to June 1, 1998

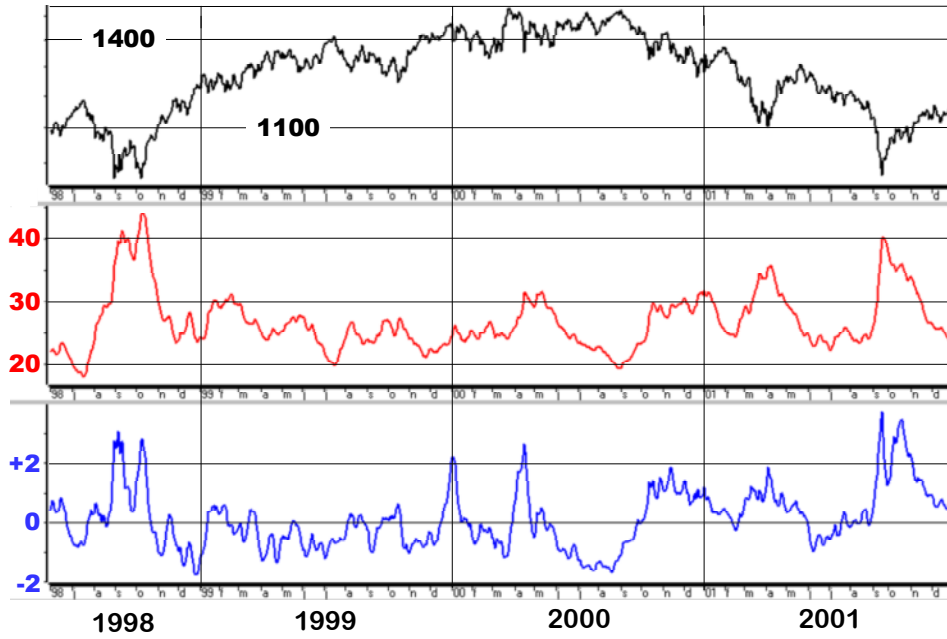
Fig. 60



S&P 500, **VIX** (exp10) & **Purified VIX** (exp10)

June 1, 1998 to Jan. 1, 2002

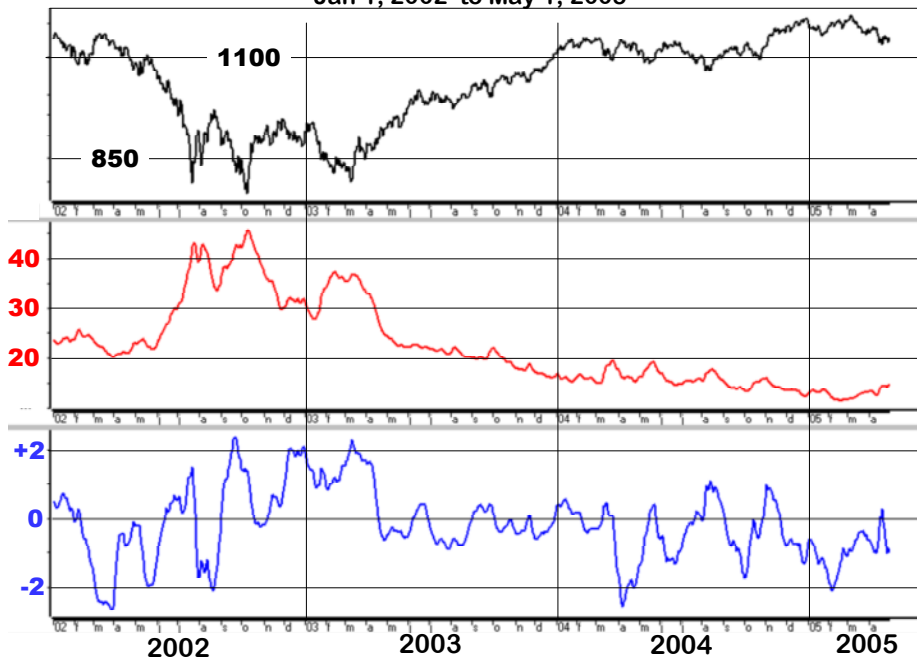
Fig. 61



S&P 500, **VIX** (exp10) & **Purified VIX** (exp10)

Jan 1, 2002 to May 1, 2005

Fig. 62



S&P 500, VIX (exp10) & Purified VIX (exp10)

May 3, 2005 to Oct. 31, 2008

Fig. 63

