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A computational implementation of stock charting: abrupt volume increase as signal for movement in New York Stock Exchange Composite Index

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Abstract

In this case study in knowledge engineering, data mining, and behavioral finance, we implement a variation of the bull flag stock charting heuristic using a template matching technique from pattern recognition to identify abrupt increases in volume in the New York Stock Exchange Composite Index. Such volume increases are found to signal subsequent increases in price under certain conditions during the period from 1981 to 1999, the Great Bull Market. A 120-trading-day history of price and volume is used to forecast price movement at horizons from 20 to 100 trading days.

Keywords: Pattern recognition; Financial decision support; Market efficiency; Technical analysis; Stock market forecasting

1. Introduction

The original Dow Theory, establishing technical analysis, was conceived and promoted by Charles Dow in the latter part of the 19th century. Ref. [3] traces the history of the Dow Theory and evaluates its effectiveness. Technical analysis includes the use of "stock charting" heuristics, which identify buy/sell signals as graphical patterns in historical price and volume values. We use template matching, a basic technique from statistical pattern recognition, to implement a variation of one charting heuristic for timing the purchase and sale of stocks. Even though the pitfalls of market timing are well known [1], we find evidence that this heuristic for market timing, in those periods in which it applies, is effective in generating returns better than a passive buy-and-hold investment strategy.

To back-test the heuristic, we use price and trading volume data for the New York Stock Exchange Composite Index, from January 28, 1981 to September, 15, 1999 (4697 trading days). This period is the Great Bull Market of the 1980s and 1990s. There is question as to whether the results may be generalized to trading range or bear market conditions, but the method is likely to be found useful in other periods for characterizing and measuring market behavior, regardless of the results of further out-of-sample testing for periods of non-bull market conditions. We see the Great Bull Market period as a useful laboratory for

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such experiments, as its general conditions continue to be uniform for a significant period of time, possibly controlling for many of the variables present in more tumultuous market periods.

This work employs a single technical analysis charting pattern, the "bull flag." The definition of "flag" from Ref. [8] is: "Technical chart pattern resembling a flag shaped like a parallelogram with masts on either side, showing a consolidation within a trend. It results from price fluctuations within a narrow range, both preceded and followed by sharp rises or declines." A bull flag pattern is then comprised of a horizontal or downward flag of "consolidation" followed by a rise, the "breakout." In this paper, we apply the bull flag pattern to trading day volume of shares (not price) in a rolling window of 120 trading days. This 120-trading-day window is about one-half of a year and is long enough for the sweeping phenomena that we are looking for to occur.

Our method is to first calculate a value for quality of fit between a template representation of the bull flag pattern and the volume values in a 120-trading-day window ending with each of the 4697 trading days in the test period. The method then uses these fit values to apply conditional trading rules, also called "filter rules," which are variations on: "If the fit value for a trading day exceeds a set value AND the price change during the period of the window has been positive (negative) then buy on that trading day, hold for some number of days, and then sell." We find that the average of the proceeds in a test period from simulated trades using these rules exceeds the average of proceeds which would have accrued if buying randomly, or, equivalently, buying on every day in the period of comparison, by a marked amount, though statistical significance may or may not be achieved, as discussed.

Note that only one charting heuristic is examined and therefore this study does not constitute a complete test of "stock charting for market timing" compared to buy-and-hold as an investment strategy. The single conditional heuristic decision rule applies only episodically, so a complete cash flow comparison with buy-and-hold over the period of the study is not appropriate. Transaction costs are not considered, and they are increasingly moot in this age of cost-free 401(k) transfers and extremely low fixed cost trades due to negotiated commission rates since 1975. Use of a broad-based market average, the New York Stock Exchange Composite Index, as the criterion variable for prediction makes adjustment for risk of individual securities unnecessary; the "systematic risk" as measured by the "beta coefficient" of the index (the portfolio) is by definition equal to 1.

2. Previous studies

Academic analyses of technical analysis, especially charting, are comparatively infrequent and sometimes somewhat hostile [18] or defensive [23]. Ref. [19] asks for an algorithmic interpretation ("knowledge engineering" in current terms) of technical analysis stock charting, which is traditionally practiced in a very subjective and noncomputational fashion. Ref. [17] tests price charting heuristics using kernel regression for pattern identification and finds marginally positive results with filter rules using 10 patterns on price. Ref. [17] evaluates performance using the distribution of returns, rather than excess profits, and work only with single-day returns.

The Efficient Markets Hypothesis (EMH) may be interpreted to mean that market prices are best described as a random walk, and past price and volume information is worthless for predicting future market price behavior. Some researchers believe that the EMH scientific research program is in what Popper terms the "degenerate" stage, and progress in understanding financial markets requires the emergence of new, positive research programs. The EMH research program and paradigm, surveyed and exemplified by Ref. [10], concentrates on developing and defending analytic models of rational expectations equilibrium which predict the end point of the process of price equilibration, assuming that the process of equilibration is instantaneous. The "anomalies" literature of "behavioral finance," surveyed by Ref. [12], includes reports of many exceptions to the assumption that the process is instantaneous, or even that it is rational. The group developing information processing models in asset markets has established a strong, new research program, surveyed in Ref. [22], which may be replacing EMH as the dominant asset markets research paradigm. The researchers in asset market information processing models are concerned with the process of market equilibration, that is, how and when the rational expectations equilibrium point is reached and how the market reasoning mechanism actually works. Much of the asset market information processing theory results from laboratory simulations and computer-based market simulation models and waits to be empirically tested, but information dissemination and aggregation have been shown to be verifiable market process phenomena. Aspects of this asset markets information processing theory model how market participants aggregate and disseminate information, and the phenomena and dimensions of interest include bubbles, false equilibria, learning dynamics, risk aversion, short-term decision horizons, market power imbalances, trader mimetics, information diffusion, decision bootstrapping, and individual trader expectations and beliefs.

Ref. [4] finds that individual stock price changes accompanied by high stock market trading volume tend to be reversed, but that this is less true of individual stock price changes associated with low stock market trading volume. Ref. [15] concludes, "Trading volume is driven mainly by non-informational trades, while stock price movements are driven primarily by informational trades." Both of these studies imply that volume is the result of factors which are not related to the intrinsic value or future price of the security. On the other hand, Ref. [5] finds "higher profits for momentum portfolios implemented on markets with higher volume in the previous period, indicating that return continuation is stronger following an increase in trading volume. This result confirms the informational role of volume and its applicability in technical analysis."

Refs. [2] and [13] are examples of studies which document positive contemporaneous correlation between trading volume and volatility, that is, absolute change in price. These studies continue the work on the mixtures-of-distributions hypothesis originally formulated in Ref. [6], by which volume and price are affected by the same "news" arrival variable so that "good news" causes a price increase and "bad news" causes a price decrease, but both good and bad news are accompanied by higher volumes in trading due to the varying interpretations of their impact by market participants as the market adjusts to a new equilibrium price. Prediction of later price based on the change in volume is not part of this work.

3. Method

Our paper concentrates on identifying abrupt volume increases, regardless of the nature of the news preceding or accompanying it, using a version of the bull flag charting heuristic. The detection of this pattern in the time series of trading volume data for the New York Stock Exchange Composite Index becomes a signal for a period of increasing price value of the New York Stock Exchange Composite Index. This signal may be regarded as an "event." Events analysis is a well-established methodology in the EMH research program [11], although events are conventionally detected as news announcements (stock splits, earnings announcements, quarterly reports, etc.) and not by pattern matching on the volume time series data.

In technical analysis, charting techniques are rarely applied to volume data systematically, as is done in this paper. The method employed is a further refinement of the method originally described in Ref. [16], but in that investigation, price was the only predictor variable used, and volume was not considered in any way. The method of application of template matching in this paper is very different from the approach of Ref. [17], and we believe that our approach is a more authentic implementation of technical analysis charting as practiced.

Fig. 1 shows the template, T, that we use to represent a variation of the bull flag stock charting pattern. This is a 10×10 grid with weights, w_{ij},

-1.5	-1.5	-1.5	-1.5	-1.5	-1.5	-1.5	**.25**	**1.25**	**4**
-1	-1	-1	-1	-1	-1	-1	**.25**	**1**	**2**
-.5	-.5	-.5	-.5	-.5	-.5	-.5	**.25**	**.75**	**1**
-.5	-.5	-.5	-.5	-.5	-.5	-.5	**.25**	0	0
-.5	-.5	-.5	-.5	-.5	-.5	-.5	0	0	0
-.25	-.25	-.25	-.25	-.25	-.25	-.25	0	0	-1
-.25	-.25	-.25	-.25	-.25	-.25	-.25	0	-.75	-1
.5	**.5**	**.5**	**.5**	**.5**	**.5**	**.5**	0	-.75	-1
2	**2**	**2**	**2**	**2**	**2**	**2**	-.5	-.75	-2
2	**2**	**2**	**2**	**2**	**2**	**2**	-.5	-.75	-2

Fig. 1. A 10×10 grid of weights used in this study to represent a variation of the bull flag charting pattern. This template is fitted or matched to 4697 120-trading-day wide windows, each fitting window ending on one of the 4697 trading days in the period of the study, from 1/28/81 to 9/15/99. We match to total daily volume values.

ranging from -2 to $+4$ in the cells. The weighting values define areas in the template for the horizontal consolidation (first seven columns) and for the upward-tilting breakout (last three columns) portions of this bull flag pattern, which are indicated by the graying in the figure. The pattern of chosen weights is regular and systematic and is consistent with the objective of depicting an abrupt increase in market volume of magnitude much greater than the general run of magnitudes immediately preceding.

The bull flag pattern template, T, is fitted or matched to the NYSE Composite Index's time series daily volume data 4697 times by taking a window of 120 total daily volume values at a time starting with the oldest daily volume value, v_1, and moving the window up 1 trading day for the next fitting. The procedure used to accomplish the fitting is *template matching* [9], a pattern recognition technique used to match a template to a pictographic image to identify objects. We let v_t be the composite's daily volume value on trading day t for the fitting window ending on trading day k, where $t = -119,\ldots,0$ and $k = 1,\ldots 4697$. For each trading day k, we synthesize a 10×10 image grid, I_k, from each set of 120 daily volume values. Next, we cross-correlate the bull flag template T with the image grid I_k and calculate a Fit_k. (Note that values for the 119 trading days preceding the first day in the 4697-trading-day test period and the values for the 99 trading days following the 4697-trading-day test period are needed to fit the first windows and for finding the profits for the last days in the test period, but these leading and trailing days are not included in the 4697 trading days for which results are reported.)

Within each 120-day window of data, we 'Winsorize variances' [20] to remove the worst noise by replacing every observation which is beyond two standard deviations from the mean of the total daily volume values in the window with the respective two standard deviation boundary value, smoothing low values for early exchange closing and for last trading days before long holidays. The method is sensitive to widely deviating values of share volume as the width of the 120-trading-day band used for fitting the template is determined by subtracting the lowest volume value in the 120 trading days from the highest.

The next step is to take the 120 days of "winsorized" daily volume values and map the information into a 10×10 image grid for the fitting window ending with trading day k. Let the image grid's gray scale values, g_{ij}, be the individual values computed into each cell of the 10×10 image grid for trading day k. These values are computed by first defining how the daily volume values will relate to the rows in the grid by calculating the range of the 120 daily volumes and dividing the range by 10 to arrive at an increment value:

$$\mathrm{inc}_k = (v_{\max} - v_{\min})/10$$

when $v_{\max}$ and $v_{\min}$ are the maximum and minimum daily volume values found within the 120 values for the window, respectively. Using this increment, we associate a row i of the image grid with an interval:

$$[v_{\max} - i{*}\mathrm{inc}_k, v_{\max} - (i-1)\mathrm{inc}_k] \quad \text{for } i = 1$$

and

$$[v_{\max} - i{*}\mathrm{inc}_k, v_{\max} - (i-1)\mathrm{inc}_k] \quad \text{for } i = 2,\ldots 10.$$

Next, we let 12 daily volume values, v_t, at a time from the 120 in the fitting window correspond to each image grid's column j. Specifically, daily volumes $v_{-12(10-j)-11}, v_{-12(10-j)-10},\ldots,v_{-12(10-j)-1}$, and $v_{-12(10-j)}$ are associated to column j, where $j = 1,\ldots 10$. Finally, the image grid's gray scale values, g_{ij}, are found for each cell in a column j by determining what portion of each column's 12 daily volume values fall into each of the 10 intervals identified by rows $i = 1,\ldots 10$. Therefore, given j, set:

$$g_{ij} = \begin{cases} 0 & \text{if none of the 12 } v_t'\text{s for column } j \text{ fall in interval } i \\ 0.085 & \text{if 1 of the 12 } v_t'\text{s for column } j \text{ fall in interval } i \\ 0.17 & \text{if 2 of the 12 } v_t'\text{s for column } j \text{ fall in interval } i \\ \ldots & \ldots \\ 0.915 & \text{if 11 of the 12 } v_t'\text{s for column } j \text{ fall in interval } i \\ 1.0 & \text{if 12 of the 12 } v_t'\text{s for column } j \text{ fall in interval } i \end{cases}$$

We now calculate the Fit_k and window price change, WPC_k, for the fitting window that ends with trading day k. Fit_k is a cross-multiplication of the template grid's weights with the image grid's gray scale values:

$$\mathrm{Fit}_k = \sum_{i=1}^{10}\sum_{j=1}^{10}(w_{ij}g_{ij})$$

Note that for the template T in Fig. 1, the highest Fit_k that could result from a fitting with 120 daily volume values is 19.5, which is the sum of the highest cell weight values in each column, and the lowest Fit_k which could result is -10.25, which is the sum of the lowest weight values in each column. Therefore, using this template, the values for Fit_k range between -10.25 and 19.5.

WPC_k is the sign of the difference between the NYSE Composite Index value (price) at the end of the last trading day of the fitting window with the price at the end of the first day of the fitting window for a trading day k, where the fitting window has 120 price values for the 120 trading days in the window. WPC_k takes the "positive" value if the closing price on the trading day at the later end of the window is greater than or equal to the closing price on the trading day at the beginning, or earlier, end of the 120-trading-day fitting window, or the "negative" value if not.

Fig. 2 shows a 10 × 10 grid overlaid on the volume values for the 120 trading days ending on 10/22/1982. These 120 values fit the template in Fig. 1 better than the values for the 120 trading days ending with any other trading day in the period of the test. The Fit_k value computed for this day is 9.25.

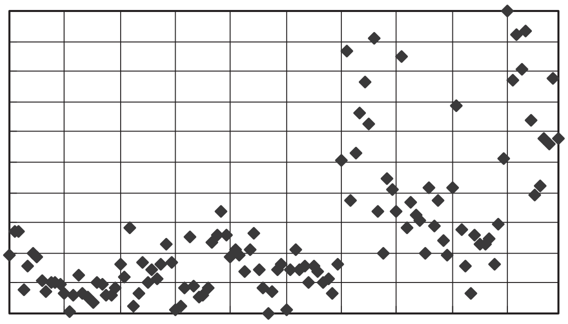

Fig. 2. A 10 × 10 grid showing volume values for best 120-trading-day window fit in the period of study. The rightmost point of the 120 points in the grid corresponds to the NYSE volume value for 10/22/1982. The fit value computed for this day is 9.25.

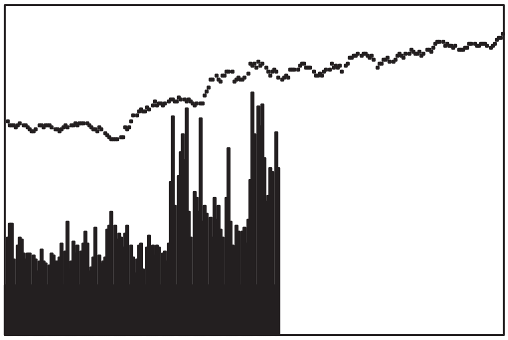

Fig. 3. Trading day is the horizontal axis. Volume is shown as vertical bars. Price (NYSE Composite Index value) is shown as points. Volume bars are shown for 120 trading days ending with 10/22/1982. Price display (NYSE Composite Index values) continues for another 100 trading days.

Fig. 3 shows the volume and the price values before and after 10/22/1982. Trading day is the horizontal axis. Volume is shown as vertical bars. Price (NYSE Composite Index value) is shown as points. Volume bars are shown for 120 trading days ending with 10/22/1982. Price display (NYSE Composite Index values) continues for another 100 trading days. Notice that the window price change, WPC_k, is positive, and the price after 100 trading days is greater than that on 10/22/1982.

We work with the test data overall and in terms of four subperiods, or data folds. The first fold begins on 1/28/1981 and is 1174 trading days long; fold 2 begins on 9/25/1985 and is 1174 days long; fold 3 begins 5/21/1990, 1174 days; fold 4, 1/13/95, 1175 trading days.

4. Initial rule results

With a broad-based composite index, the overall average price (index value) increase/decrease in the period is equivalent to the return from a buy-and-hold or random-selection trading strategy, which is implied as optimal by the random walk model of the Efficient Markets Hypothesis. We test the results of applying a trading rule by comparing to the results of buying on every day in the period of comparison and holding for the number of trading days in the horizon specified in the trading rule. To determine if placing buy orders when directed by the heuristic is

Table 1
Results from applying the method to the first test data fold and holding the indicated purchases for 60 trading days

Rule	Volume fit ≥	Window price change	Test data fold	Number of buys	Profit (%)	Excess profit (%)	*P*-value
1	− 99	all	1	1174	2.3	0.0	0.500000
2	− 99	negative	1	455	0.9	− 1.4	0.003422
3	− 99	positive	1	719	3.1	0.9	0.003015
4	0	negative	1	96	− 2.6	− 4.9	0.000000
5	0	positive	1	233	4.0	1.7	0.000085
6	2	negative	1	5	11.1	8.8	0.110888
7	2	positive	1	116	7.3	5.0	0.000000
8	4	negative	1	0			
9	4	positive	1	76	9.7	7.4	0.000000

The excess profit value in the cell is the difference between the Market Average Return, which is the average profit realized by buying on every day, and the Trading Rule Average Return, which is the average profit realized by buying only on the rule-indicated days. Both market strategies buy and hold for the number of trading days in the horizon period, which is 60 days here. Results for several trading rules are shown. For example, trading rule 9 is, "For a trading day k if $\text{Fit}_k \geq 4$ and WPC_k is positive then buy and hold for 60 trading days." The application of trading rule 9 in test data fold 1 resulted 76 indicated purchases and in 7.4% profit in excess of what would have realized by buying the same number of times on randomly chosen trading days, and the probability of achieving this excess profit by random sampling (*P*-value) is 0.000000.

better than buying every day or at random (the trading policies indicated as optimal by the efficient markets hypothesis), we calculate the profit using the heuristic method and for buying every day.

Let:

v_k a NYSE Composite Index volume value on trading day k

p_k a NYSE Composite Index (price) value on trading day k

Fit_k a fit value computed as described above for trading day k

h number of trading days in the forecast horizon, where $h = 20, 40, 60, 80, 100$

where

k 1,. . .,4697 for the trading days in the period of the study and $k = 1$ corresponds to the date 1/28/1981

m the first trading day k in a subperiod of comparison

n the last trading day k in a subperiod of comparison.

Calculate results for a subperiod, s, when buying every day:

$$\text{Market Average Return}_s = \sum_{k=m}^{n} [(p_{k+h} - p_k)/p_k] / (n - m + 1)$$

Table 2
Results for 60-day horizon (holding period) for all rules by test data fold

Rule	Volume fit ≥	Window price change	Test data fold	Number of buys	Profit (%)	Excess profit (%)	*P*-value
1	− 99	all	1	1174	2.3	0.0	0.500000
	− 99	all	2	1174	3.2	0.0	0.500000
	− 99	all	3	1174	1.7	0.0	0.500000
	− 99	all	4	1175	4.6	0.0	0.500000
2	− 99	negative	1	455	0.9	− 1.4	0.003422
	− 99	negative	2	268	5.3	2.0	0.000000
	− 99	negative	3	288	5.0	3.3	0.000000
	− 99	negative	4	89	10.7	6.1	0.000000
3	− 99	positive	1	719	3.1	0.9	0.003015
	− 99	positive	2	906	2.6	− 0.6	0.057898
	− 99	positive	3	886	0.6	− 1.1	0.000000
	− 99	positive	4	1086	4.1	− 0.5	0.027040
4	0	negative	1	96	− 2.6	− 4.9	0.000000
	0	negative	2	30	4.0	0.8	0.202941
	0	negative	3	43	2.5	0.8	0.211366
	0	negative	4	54	13.6	8.9	0.000000
5	0	positive	1	233	4.0	1.7	0.000085
	0	positive	2	250	4.7	1.4	0.014780
	0	positive	3	331	0.8	− 0.9	0.000371
	0	positive	4	354	4.3	− 0.3	0.136417
6	2	negative	1	5	11.1	8.8	0.110888
	2	negative	2	29	3.6	0.4	0.332469
	2	negative	3	10	− 1.3	− 3.0	0.000789
	2	negative	4	30	15.4	10.8	0.000000
7	2	positive	1	116	7.3	5.0	0.000000
	2	positive	2	35	7.9	4.6	0.000000
	2	positive	3	50	− 0.8	− 2.5	0.000060
	2	positive	4	24	1.0	− 3.6	0.000032
8	4	negative	1	0			
	4	negative	2	28	4.2	1.0	0.072922
	4	negative	3	0			
	4	negative	4	0			
9	4	positive	1	76	9.7	7.4	0.000000
	4	positive	2	2	12.1	8.8	0.000263
	4	positive	3	0			
	4	positive	4	0			

Excess profit and *P*-value are computed for the individual fold subperiods.

Table 3
Results for 60-day horizon (holding period) for all rules overall for the complete testing period from January 28, 1981 to September 15, 1999 (4697 trading days)

Rule	Volume fit ≥	Window price change	Number of buys	Profit (%)	Excess profit (%)	*P*-value
1	− 99	all	4697	3.0	0.0	0.500000
2	− 99	negative	1100	3.9	0.9	0.000419
4	0	negative	223	3.2	0.2	0.354775
6	2	negative	74	8.3	5.3	0.000001
8	4	negative	28	4.2	1.3	0.026739
3	− 99	positive	3597	2.7	− 0.3	0.037508
5	0	positive	1168	3.3	0.4	0.036695
7	2	positive	225	4.9	2.0	0.000003
9	4	positive	78	9.8	6.8	0.000000

Then calculate results when buying as specified by the trading rule. First,

$$\text{Number of Buys}_s = \sum_{k=m}^{n} R_k$$

where

$$R_k = \begin{cases} 1 & \text{if trading rule is true for Fit}_k \text{ and WPC}_k \\ 0 & \text{otherwise} \end{cases}$$

Thus,

$$\text{Trading Rule Average Return}_s = \sum_{k=m}^{n} [((p_{k+h} - p_k)R_k)/p_k]/\text{Number of Buys}_s$$

Finally, we have "excess" profits for the subperiod s:

$$\text{Excess Profits}_s = \text{Trading Rule Average Return}_s - \text{Market Average Return}_s$$

We compare Market Average Return to Trading Rule Average Return using a two-sample, one-tailed, unequal variance (heteroscedastic) Student's *t*-test. The first row of Table 1 reports the excess profit obtained from applying the results of the fitting process as the trading rule, "For a trading day k if $\text{Fit}_k \geq -99$ and for any WPC_k value buy and hold for 60 trading days," to the 4697 trading days in our test period. The -99 parameter value used in this rule is less than the lowest fit value possible, so this rule does not filter at all on fit value, nor does this rule filter based on the price change in the window. The resulting excess profit value is 0.0% because this rule buys on every day of the subperiod, which is test data fold 1 for Table 1.

Rule 2, reported in the second row of Table 1, is "For a trading day k, if $\text{Fit}_k \geq -99$ and Window Price Change_k is negative, buy and hold for 60 trading days." The excess profit shown is -1.4% for rule 2 for test data fold 1. Rule 2 indicated buying 455 times out of the 1174 days in test data fold 1, and the *t*-test probability value (*P*-value) is 0.003422 for the comparison of the 0.9% profit obtained from application of Rule 2 with the 2.3% profit resulting from buying on every trading day and holding for 60 days. (The method used for computing statistical

Table 4
Results for 20-, 40-, 60-, 80-, and 100-trading-day horizon (holding period) for rules 8 and 9

Rule	Volume fit ≥	Window price change	Horizon (holding period)	Profit (%)	Excess profit (%)	Annualized excess profit (%)	*P*-value
8	4	negative	20	− 1.3	− 2.3	− 25.4	0.011728
	4	negative	40	2.0	0.1	0.5	0.451011
	4	negative	60	4.2	1.3	5.4	0.026739
	4	negative	80	9.2	5.2	17.1	0.000000
	4	negative	100	9.2	4.2	10.8	0.000010
9	4	positive	20	4.1	3.1	45.9	0.000000
	4	positive	40	7.9	5.9	43.3	0.000000
	4	positive	60	9.8	6.8	31.7	0.000000
	4	positive	80	12.5	8.5	29.2	0.000000
	4	positive	100	15.7	10.7	29.0	0.000000

The number of indicated buys for rule 8 is 28 and for rule 9 is 78.

significance here may be biased in favor of the method, and this is discussed in the next section of the paper.)

Rule 3, the same as Rule 2 except for positive window price change, WPC_k, resulted in 719 buys in the first test data fold and an excess profit of 0.9%, with a P-value of 0.00342. Positive price momentum also holds in test data fold 1. Rules 4 through 9 require higher levels of Fit_k. Excess profit generally increases as the requirement for Fit_k is increased. The interaction between WPC_k and Fit_k is not easy to discern in Table 1.

Table 2 contains results for a 60-trading-day holding period for all of the rules for all of the test data folds. Rules 2 and 3 show that for the later three folds, price momentum does not hold true, and mean reversion occurs instead. The hypothesis that higher fit results in higher excess profit holds well for the first two test data folds, but not so well for the latter two.

Table 3 shows cumulative results for the complete testing period (all four test data folds) for a 60-trading-day horizon (buy on rule-indicated days and hold for 60 trading days). The hypothesis that higher Fit_k requirement is associated with higher excess profit appears to hold well for *positive* window price change, WPC_k, but not as well for *negative* WPC_k. The excess profit and P-value results for rules 3 and 4 are measures of the overall strength of the mean reversion phenomenon at the 60-day forecast horizon in this test sample. The strength of the overall support in these results for the hypothesis that better volume fit signals a price rise for a positive window price change (overcoming mean reversion) shows clearly in Table 3.

Table 4 contains overall results for trading rules 8 and 9 for all horizons in this study (20, 40, 60, 80, and 100 trading days). Higher fit values appear to result in higher excess profits at the longer horizons for negative window price change and at all horizons for the trading rule requirement of positive window price change. “Annualized Excess Profit” shows excess profit annualized on a 250-trading-day-per-year basis. The annualized excess profit column reveals that rule 9, positive window price change, performs best for the shorter horizons. Interestingly, rule 8, negative window price change, shows highly negative excess profit for the 20-trading-day forecast horizon (purchase holding period).

Table 5 shows results for all trading rules by test data fold for the 100-trading-day horizon. For negative window price change, excess profits are not seen to exceed the baseline results (rule 2) until the higher fit requirements of trading rules 6 and 8 are used. In

Table 5
Results for 100-day horizon (holding period) for the individual test data folds

Rule	Volume fit ≥	Window price change	Test data fold	Number of buys	Profit (%)	Excess profit (%)	P-value
1	− 99	all	1	1174	4.1	0.0	0.500000
	− 99	all	2	1174	4.7	0.0	0.500000
	− 99	all	3	1174	3.4	0.0	0.500000
	− 99	all	4	1175	7.7	0.0	0.500000
2	− 99	negative	1	455	2.6	− 1.5	0.009992
	− 99	negative	2	268	6.7	1.9	0.000327
	− 99	negative	3	288	8.2	4.7	0.000000
	− 99	negative	4	89	14.4	6.7	0.000000
3	− 99	positive	1	719	5.0	0.9	0.015104
	− 99	positive	2	906	4.2	− 0.6	0.123260
	− 99	positive	3	886	1.9	− 1.5	0.000000
	− 99	positive	4	1086	7.1	− 0.5	0.038930
4	0	negative	1	96	− 2.7	− 6.8	0.000000
	0	negative	2	30	8.9	4.2	0.000102
	0	negative	3	43	5.5	2.1	0.041412
	0	negative	4	54	16.1	8.5	0.000000
5	0	positive	1	233	8.5	4.4	0.000000
	0	positive	2	250	8.5	3.8	0.000000
	0	positive	3	331	1.4	− 2.0	0.000000
	0	positive	4	354	8.3	0.6	0.054521
6	2	negative	1	5	12.2	8.1	0.195042
	2	negative	2	29	8.6	3.9	0.000216
	2	negative	3	10	0.2	− 3.2	0.006927
	2	negative	4	30	17.2	9.5	0.000000
7	2	positive	1	116	13.0	9.0	0.000000
	2	positive	2	35	8.2	3.5	0.000241
	2	positive	3	50	− 0.5	− 3.9	0.000000
	2	positive	4	24	11.7	4.0	0.000020
8	4	negative	1	0			
	4	negative	2	28	9.2	4.4	0.000006
	4	negative	3	0			
	4	negative	4	0			
9	4	positive	1	76	15.8	11.7	0.000000
	4	positive	2	2	12.4	7.7	0.025847
	4	positive	3	0			
	4	positive	4	0			

Like Table 2, but for horizon of 100 trading days rather than 60 days. Excess profit and P-value are computed for the individual fold subperiods.

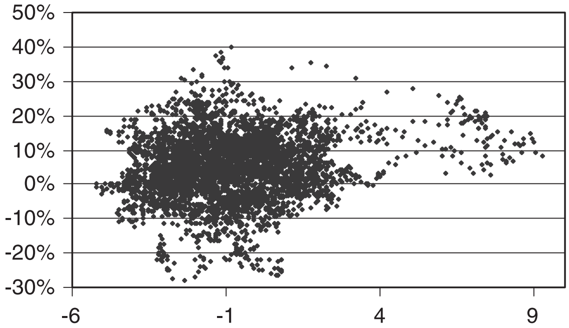

Fig. 4. All 4697 trading days in the study are plotted. Volume fit is on the horizontal axis, and profit at a horizon of 100 trading days is on the vertical axis. The overall average 100-trading-day profit is 4.97%. The volume fit appears to be somewhat effective at differentiating the trading days on their future profitability, chiefly by removing the lowest profitability days in the region of higher volume fit values, on the right-hand side of the graph.

fact, all of the excess profits for negative window price change might be attributed to mean reversion and none to the association with higher fit values. However, excess profits for positive window price change appear to exceed the baseline results (rule 3) for all higher number rules (5, 7, and 9). Test data fold 3 has opposite results for rules 5, 6, and 7—the Gulf War occurred during test data fold 3, and this might be a factor.

Fig. 4 shows 100-trading-day profit for all of the days in the study. Each point in Fig. 4 represents one of the 4697 trading days. The overall average 100-day profit is 4.97%. The volume fit appears to be somewhat effective at differentiating the trading days on their future profitability by removing the lowest profitability days with the higher volume fit values. Fig. 5 shows the 100-trading-day profit for the subset of the trading days represented in Fig. 4 that have a negative window price change, and Fig. 6 shows the same for those trading days with positive price change. A difference between the plots in Figs. 5 and 6 may be seen. The very lowest profit values are missing from Fig. 5, and the very highest are missing from Fig. 6, a marked "reversion to the mean." But the higher volume fit values are accompanied by higher 100-trading-day profits in Fig. 6, for the positive window price change, than in Fig. 5.

Table 6 is the same layout as Table 5, but the results are for a 20 trading horizon (holding period). Interpretation of these results is difficult—the story is mixed for this shorter horizon.

Table 7 contains overall results for all rules with *negative* window price change for all horizons. The hypothesis that higher Fit_k values are associated with higher excess profit values appears to hold up to a Fit_k value of 2 (rule 6) for all horizons, and then the excess profit values recede, though they remain positive for horizons of 80 and 100 trading days. That excess profits are impressively negative for high Fit_k, and negative window price change for a horizon of 20 trading days is an interesting finding and deserves further study, but there are too few

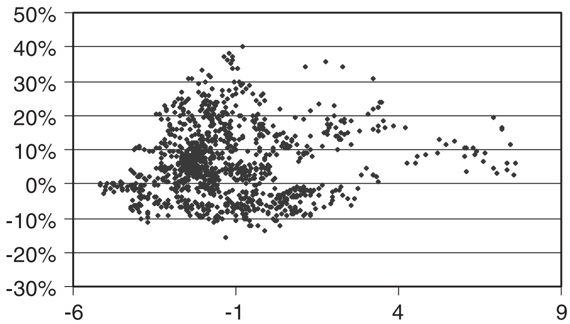

Fig. 5. A subset of the points on Fig. 4 are plotted. Volume fit is on the horizontal axis and 100-trading-day profit on the vertical axis. Points represent only those trading days preceded by a *negative* window price. Note that the lowest profit values seen on Fig. 4 are missing here.

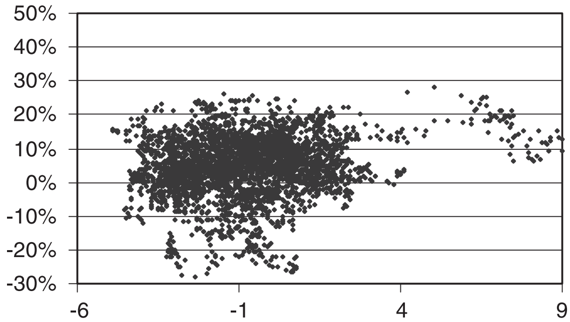

Fig. 6. A subset of the points on Fig. 4 are plotted. Volume fit is on the horizontal axis and 100-trading-day profit is on the vertical axis. Points represent only those trading days preceded by a *positive* window price. Note that the highest profit values seen on Fig. 4 are missing here.

Table 6
Results for 20-day horizon (holding period) for the individual test data folds

Rule	Volume fit ≥	Window price change	Test data fold	Number of buys	Profit (%)	Excess profit (%)	*P*-value
1	− 99	all	1	1174	0.7	0.0	0.500000
	− 99	all	2	1174	1.2	0.0	0.500000
	− 99	all	3	1174	0.5	0.0	0.500000
	− 99	all	4	1175	1.5	0.0	0.500000
2	− 99	negative	1	455	0.3	− 0.5	0.038007
	− 99	negative	2	268	2.1	0.9	0.000688
	− 99	negative	3	288	1.6	1.1	0.000004
	− 99	negative	4	89	3.6	2.1	0.000071
3	− 99	positive	1	719	1.0	0.3	0.061237
	− 99	positive	2	906	0.9	− 0.3	0.117189
	− 99	positive	3	886	0.1	− 0.4	0.003034
	− 99	positive	4	1086	1.4	− 0.2	0.129766
4	0	negative	1	96	0.5	− 0.2	0.363051
	0	negative	2	30	− 1.5	− 2.6	0.008673
	0	negative	3	43	0.7	0.2	0.345072
	0	negative	4	54	4.2	2.6	0.001092
5	0	positive	1	233	1.7	0.9	0.000624
	0	positive	2	250	1.8	0.6	0.012951
	0	positive	3	331	0.1	− 0.4	0.005478
	0	positive	4	354	0.7	− 0.8	0.000141
6	2	negative	1	5	7.7	7.0	0.002733
	2	negative	2	29	− 1.8	− 2.9	0.003986
	2	negative	3	10	− 3.1	− 3.5	0.000333
	2	negative	4	30	6.7	5.2	0.000039
7	2	positive	1	116	3.1	2.4	0.000000
	2	positive	2	35	1.1	− 0.1	0.417049
	2	positive	3	50	− 0.2	− 0.7	0.031919
	2	positive	4	24	2.3	0.7	0.067385
8	4	negative	1	0			
	4	negative	2	28	− 1.3	− 2.5	0.007658
	4	negative	3	0			
	4	negative	4	0			
9	4	positive	1	76	4.2	3.5	0.000000
	4	positive	2	2	− 1.3	− 2.5	0.067028
	4	positive	3	0			
	4	positive	4	0			

Like Table 2, but for horizon of 20 trading days rather than 60 days. Excess profit and *P*-value are computed for the individual fold subperiods.

indicated buys to consider this a nonspurious result. Unknown factors not included in the study appear to be strong in the case of a negative window price change.

Table 8 contains overall results for all rules with *positive* window price change for all horizons. The hypothesis that higher excess profit values are associated with higher levels of fit is consistently and systematically supported by these overall results.

5. Buying runs and statistical significance

The operational premise of the preceding analysis is that the decision to buy at the beginning of the next trading day is made after the market is closed on the preceding day. A trading day's closing price and volume values along with the preceding 119 days of price and volume data constitute the database which is input to the purchase decision for the following morning. The value of the decision made for any previous trading days is not an explicit input to the decision making. Thus, the result of the decision to buy, or not, for each trading day may be considered to be independent of the result of the decision to buy, or not, for any preceding trading day, and that is the assumption used in the statistical analysis presented in Tables 1–8.

However, the naive computation of statistical significance used in Tables 1–8 may not be correct. The database used for making the purchase decision for 1 day is almost identical to the database for the preceding trading day as price and volume values for 119 out of the 120 trading days represented within it. A similar situation exists on the forecast horizon side of the moving window. The price change for the 60-day interval, for example, following a trading day is quite closely related to the same change for the next trading day. These dependencies are not consistent with the use of the *t*-test to determine the significance of the difference between the overall average profit and the average profit for all trading days selected by the filter rules.

In this study the filter rules often recommend purchase in succeeding days, resulting in "buying runs." Table 9 shows the number of such buying runs and the average length of such runs in trading days for trading conditioned on volume fit values greater than or equal to 2, 3, and 4. Average run lengths range from 9 to 28 trading days.

A case can be made that for a trader, each trading day is a new decision-making situation. For a trader using these rules, as a pattern develops, the trader could see additional opportunity and invest again each

Table 7
Overall results for rules with *negative* window price change for all horizons for complete testing period

Rule	Volume fit ≥	Window price change	Horizon (holding period)	Number of buys	Profit (%)	Excess profit (%)	Annualized excess profit (%)	*P*-value
2	−99	negative	20	1100	1.3	0.3	4.4	0.009668
4	0	negative	20	223	1.2	0.2	2.6	0.283024
6	2	negative	20	74	2.1	1.2	15.4	0.078958
8	4	negative	20	28	−1.3	−2.3	−25.4	0.011728
2	−99	negative	40	1100	2.6	0.6	4.1	0.000881
4	0	negative	40	223	2.8	0.8	5.2	0.053475
6	2	negative	40	74	5.7	3.7	25.7	0.000052
8	4	negative	40	28	2.0	0.1	0.5	0.451011
2	−99	negative	60	1100	3.9	0.9	3.8	0.000419
4	0	negative	60	223	3.2	0.2	1.0	0.354775
6	2	negative	60	74	8.3	5.3	24.0	0.000001
8	4	negative	60	28	4.2	1.3	5.4	0.026739
2	−99	negative	80	1100	5.0	1.0	3.2	0.000434
4	0	negative	80	223	4.4	0.4	1.3	0.260141
6	2	negative	80	74	11.0	7.1	23.8	0.000000
8	4	negative	80	28	9.2	5.2	17.1	0.000000
2	−99	negative	100	1100	6.0	1.0	2.6	0.001018
4	0	negative	100	223	5.0	0.0	0.1	0.475826
6	2	negative	100	74	11.2	6.2	16.3	0.000000
8	4	negative	100	28	9.2	4.2	10.8	0.000010

day. But it is clear that the *t*-test probability values shown in Tables 1–8 are likely to be lower bounds on what these values might actually be. To establish a possible upper bound, Table 10 reports probability values computed in the same way except that only the first day of each buying run is used, and the data for

Table 8
Overall results for rules with *positive* window price change for all horizons for complete testing period

Rule	Volume fit ≥	Window price change	Horizon (holding period)	Number of buys	Profit (%)	Excess profit (%)	Annualized excess profit (%)	*P*-value
3	−99	positive	20	3597	0.9	−0.1	−1.3	0.115496
5	0	positive	20	1168	0.9	0.0	−0.5	0.366751
7	2	positive	20	225	2.0	1.0	13.2	0.000053
9	4	positive	20	78	4.1	3.1	45.9	0.000000
3	−99	positive	40	3597	1.8	−0.2	−1.2	0.055809
5	0	positive	40	1168	2.1	0.2	1.1	0.164200
7	2	positive	40	225	3.3	1.3	8.3	0.000582
9	4	positive	40	78	7.9	5.9	43.3	0.000000
3	−99	positive	60	3597	2.7	−0.3	−1.1	0.037508
5	0	positive	60	1168	3.3	0.4	1.6	0.036695
7	2	positive	60	225	4.9	2.0	8.5	0.000003
9	4	positive	60	78	9.8	6.8	31.7	0.000000
3	−99	positive	80	3597	3.7	−0.3	−1.0	0.038272
5	0	positive	80	1168	4.9	0.9	2.9	0.000066
7	2	positive	80	225	6.9	2.9	9.5	0.000000
9	4	positive	80	78	12.5	8.5	29.2	0.000000
3	−99	positive	100	3597	4.7	−0.3	−0.8	0.051307
5	0	positive	100	1168	6.4	1.5	3.7	0.000000
7	2	positive	100	225	9.2	4.2	10.8	0.000000
9	4	positive	100	78	15.7	10.7	29.0	0.000000

Table 9
Buying run statistics

Volume fit ≥	Window price change	Number of trading days	Number of buy days	Number of runs	Average run length
2	all	4697	299	30	10.0
	negative	1100	74	7	10.6
	positive	3597	225	25	9.0
3	all	4697	153	10	15.3
	negative	1100	46	4	11.5
	positive	3597	107	7	15.3
4	all	4697	106	4	26.5
	negative	1100	28	1	28.0
	positive	3597	78	3	26.0

Due to the nature of the method, positive buying recommendations frequently occur on sequential days, resulting in "buying runs," making computation of statistical significance difficult.

the other buy days in the run are discarded. Even with an adjustment in significant requirements for the small size of the sample resulting from the use of only the run first days, statistical significance is generally not achieved, though the results are suggestive of worth for higher minimum fit values and for larger trading horizons.

Table 10 also includes the proportion of first run day positive excess returns. If the rules were ineffective and returns were distributed evenly about the mean, the expectation would be that only half of the time, on average, would positive excess returns be achieved. The proportions reported in Table 10 are generally higher than 50% for the higher fit values, but with the small sample size, we do not compute statistical significance. Ref. [7] points out, concerning technical trading rules:

> These types of rules will tend to place the investor on the 'right' side of long, sustained movements in market prices, and on the 'wrong' side of short, transitory movements. A technical forecaster's performance may thus be marked by a relatively small number of successful forecasts (where large profits are made) and a relatively large number of incorrect predictions (where small losses are incurred). Clearly the fact that the number of incorrect predictions is larger than the number of correct forecasts is not sufficient in this situation to rule out the possibility of forecast value.

Likewise, that the number of correct predictions is comparatively large does not necessarily mean that forecast value is present.

The computation of significance using all of the days on which purchases are recommended may be too favorable to the method, as independence assumptions of the test used are violated. The computation which considers only the first day of buying runs is likely to be too strict, as much data favorable to the method is discarded. The true statistical significance may lie somewhere in between these two bounds. Refs. [7] and [21] examine the problems of trading rule evaluation and computation of statistical significance; the problem is complex, the solution lies beyond the correct selection of a statistical test, and much methodological work remains to be done.

An element of a logical paradox exists in this consideration of the need for an alternative computation of statistical significance. If the EMH is correct in the main and price and volume follow random walks, then it would seem that the computation of statistical significance as performed for Tables 1–8 approximates the correct values more nearly than if the EMH is less correct.

In addition, Table 10 contains statistics computed using the sums of differences in profit averages for the days sequentially denominated "1" through "120." The first day in the 4697 trading days in the period of the study is assigned a "1," and the second day is assigned a "2," and so forth, up to "120," when the 121st day in the period is assigned a "1," and the 122nd day is assigned a "2," and so forth, until all 4697 days are associated with a numeral "1" through "120." The average profit for each trading day with the number "27," for example, is computed (a) overall and (b) for those days on which a buy is recommended. The sum of the differences between the paired average profit values, (a) and (b), for each of the 120 denominated days adjusted for the standard deviation of the differences between the pairs and for the degrees of freedom becomes the t-statistic for computation of significance. On the face of it, this test compensates for the independence problems resulting from the overlap in the 120-day fitting window and in the period of the holding period. The significance values thus computed are higher than the ones shown in Tables 1–8 but are lower than those computing using only the first days of the buying runs. For the higher

Table 10
Buying run first day and paired t-test results

Volume fit ≥	Window price change	Trading horizon	First day of run only				Paired t-test (all buys)	
			Average excess profit (%)	P-value	N	Days with positive excess (%)	Sum of differences (%)	P-value
2	all	20	−0.2	0.389534	30	47	1.0	0.104361
	negative	20	0.4	0.458378	7	43	0.7	0.299425
	positive	20	−0.3	0.303520	25	48	0.6	0.190925
	all	60	1.2	0.227815	30	47	2.5	0.014124
	negative	60	5.7	0.170000	7	57	3.9	0.038899
	positive	60	0.1	0.458979	25	44	1.7	0.134402
	all	100	0.8	0.318951	30	43	4.7	0.000675
	negative	100	5.7	0.187495	7	57	5.5	0.017074
	positive	100	−0.1	0.461930	25	40	3.9	0.022876
3	all	20	2.9	0.054670	10	70	1.8	0.037574
	negative	20	6.2	0.085691	4	75	0.7	0.299907
	positive	20	1.6	0.108209	7	71	1.8	0.036482
	all	60	5.2	0.037960	10	70	5.4	0.000003
	negative	60	10.7	0.069518	4	75	2.9	0.070432
	positive	60	3.5	0.089371	7	71	6.4	0.000000
	all	100	5.1	0.067410	10	60	8.4	0.000000
	negative	100	13.0	0.048060	4	75	6.1	0.001185
	positive	100	3.0	0.213248	7	57	9.2	0.000000
4	all	20	3.1	0.117754	4	75	1.4	0.180504
	negative	20	6.4		1	100	−2.5	0.128973
	positive	20	2.0	0.255876	3	67	2.9	0.016232
	all	60	6.7	0.080374	4	75	5.2	0.000656
	negative	60	4.3		1	100	−0.5	0.369500
	positive	60	7.5	0.135649	3	67	7.5	0.000000
	all	100	10.1	0.061497	4	75	9.1	0.000000
	negative	100	11.2		1	100	3.7	0.029406
	positive	100	9.7	0.141585	3	67	11.3	0.000000

"First day of run only" statistics are calculated using only the data for the first days of buying runs, discarding the data for the other days in the run. N is the number of runs, therefore, the number for first days. "Paired t-test (all buys)" columns refer to statistics computed using the sums of differences in profit averages for the days "1" through "120." Each of the 4697 trading days in the period of the study are assigned a number "1" through "120" in sequential fashion. The average profit for each trading day with the number "27," for example, is computed (a) overall and (b) for those days on which a buy is recommended. The sum of the differences between the two average profit values for each of the 120 numerically denominated days adjusted for standard deviation and degrees of freedom becomes the t value for computation of significance.

volume fit minimums and for "all" and "positive" window price change, statistical significance is found.

6. Discussion

Most of the previous related work works only with single-day returns. The results in this paper indicate that longer return horizons, in multiple months, should be examined.

In a previous study [5] which is closely related to our work, the finding that "higher profits for momentum portfolios implemented on markets with higher volume in the previous period, indicating that return continuation is stronger following an increase in trading volume" is consistent with our finding that excess returns are positive for better bull flag template volume fit, especially when the window price change is positive. Ref. [15] finds that "trading volume is driven mainly by non-informational trades, while stock price movements are driven primarily by informational trades." Our observations that an abrupt increase in volume (higher bull flag template volume fit) accompanied by an increasing price (positive window price change) presages a market price increase at all horizons, but more strongly at the shorter terms, implies that both volume and price behavior are likely to be the result of ‘‘informational’’ trades, in this case, quite possibly the result of strong market pressure to get into the market at an opportune time. In addition, the association of high volume fit and negative window price change with a short-term price decline (see the 20-day trading horizon entries in Table 7) may imply informed pressure to leave the market, although too few cases of this are found in this study to support strong assertion of this. In neither of these cases is the abrupt increase in trading volume likely to be ‘‘non-informational,’’ or noise, trading, but there are stronger unknown factors at work in the case of negative window price change.

We consider the complete test period used in this paper to be ‘‘out-of-sample,’’ given that the ‘‘bull flag’’ heuristic has been around for quite a long time and our template representation is quite typical and true to the technical analysis literature. The template weights are assigned to be regular and systematically related to the objective of detecting an abrupt volume increase. The template weights and other parameters in the study do not show anomalies which are usually present in tuned or ‘‘snooped’’ work.

We are unsure as to exactly what economic mechanisms are manifesting themselves here. Asset markets information processing research is in an early stage of development, collecting experimental results and endeavoring to induce some new theory or draw a useful correspondence with some established theory. Our experiments fall into that data collection phase of theory construction.

Ref. [11] says of work which challenges the EMH:

> A problem in developing an overall perspective on long-term return studies is that they rarely test a specific alternative to market efficiency. Instead, the alternative hypothesis is vague, market inefficiency. This is unacceptable. Like all models, market efficiency (the hypothesis that prices fully reflect available information) is a faulty description of price formation. Following the standard scientific rule, however, market efficiency can only be replaced by a better specific model of price formation, itself potentially rejectable by empirical tests.

Koopmans [14], however, believes in the value of contributions that merely find empirical relationships and do not necessarily propose new theory, implying that the discipline of Finance as characterized by the EMH research program is in a ‘‘pre-Kepler’’ stage:

> Kepler’s outstanding success was due to a willingness to strike out for new models and hypotheses if such were needed to account for the observations obtained. He was able to find simple empirical ‘laws’ which were in accord with past observations and permitted the prediction of future observations. This achievement was a triumph for the approach in which large scale gathering, sifting, and scrutinizing of facts precedes, or proceeds independently of, the formulation of theories and their testing by further facts.

In a vein that might be considered as a manifesto for data mining, Koopmans continues:

> The terms ‘empirical regularities’ and ‘fundamental laws’ are used suggestively to describe the ‘Kepler stage’ and the ‘Newton stage’ of the development of celestial mechanics. It is not easy to specify precisely what is the difference between the two stages. Newton’s law of gravitation can also be looked upon as describing an empirical regularity in the behavior of matter. The conviction that this ‘law’ is in some sense more fundamental, and thus constitutes progress over the Kepler stage, is due, I believe, to its being at once more elementary and more general. It is more elementary in that a simple property of mere matter is postulated. As a result, it is more general in that it applies to all matter, whether assembled in planets, comets, sun or stars, or in terrestrial objects—thus explaining a much wider range of phenomena.

Continuing the physics analogy (which is not uncommonly used in describing stock market behavior: ‘‘market momentum’’ and ‘‘reversal,’’ implying spring oscillation), by studying a broad market index, we are approaching the stock market as a pile of sand, with each grain of sand being a single share of stock. The grains of sand vary in size, shape, density, and resiliency. Projectiles of different sizes, speeds, masses, and makeup are constantly pelting into the pile, striking varying sized groups of grains in various directions and with varied force. In this paper, we are trying to predict the position of the whole pile at a point of time in the future using knowledge of how the pile has changed direction in the past (window price change) and a count of how many grains moved each day (trading volume) in the past. We are looking to detect that a large bulldozer collided at high speed with the sand pile (an abrupt increase in trading volume) and, based on that event analysis, to forecast the sand pile's movement. The problem is made more difficult by the presence of many projectiles, including other bulldozers, in the area.

In the Great Bull Market of the 1980s and 1990s, most of the big bulldozer hits drove the sand pile in the positive direction, but its previous direction (momentum?) affected how far it was moved. We certainly suspect interest rates as a frequent driver of the bulldozers, and we will examine that conjecture in future work in fleshing out our "stock market as sand pile" theory.

7. Conclusion

We test a bull flag volume charting heuristic for trading the NYSE Composite Index in a rigorous way for the period of the Great Bull Market of the 1980s and 1990s. The hypothesis that better bull flag template volume fit is associated with higher excess profits is supported by the experimental results in the case of a positive window price change (increase in price during the 120 trading days of the fitting window, that is, the 120-trading-day period preceding and including the trading day of interest). Overall results are systematic and suggestive that the method has some forecasting ability. Results by test data fold are less strong, especially for test data fold 3 (in which the Gulf War occurred). Results are generally more consistent for the longer forecast horizons. Annualized excess profitability results are stronger for the shorter forecast horizons.

The results presented herein encourage us to consider our investigation of stock charting as a technique for predicting stock market price behavior. Further work is needed to find if consistent or stronger/weaker results may be found with window widths shorter and longer than 120 trading days, for other forecast horizons and for other back-test periods. Other templates and other variations on the bull flag and other charting heuristic templates on volume and/or price will also be tested in future work, and we intend to look at the use of interest rate and other macroeconomic variables as predictor factors in conjunction with this method.

In addition to possible economic value to stock traders, this work may contribute a research tool to the asset markets information processing research program and may contribute to accrediting the practitioner literature on technical analysis and stock charting as a valuable knowledge source for formulating conjectures about dynamic stock market behavior.

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