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Implementation and validation of an opportunistic stock market timing heuristic: One-day share volume spike as buy signal

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Abstract

This paper presents the results of simulated trading on long time series price and share volume data for the Dow Jones Industrial Average and Standard and Poor's 500 Index. Robust and systematic results demonstrate strong support for the effectiveness of the market trading heuristic of buying when one-day share trading volume spikes. Implementation of the methods is straightforward and may be readily accomplished with spreadsheet technology for decision support applications.

Keywords: Heuristics; Forecasting; Decision support systems; Expert systems

1. Introduction

We present a method for computational implementation and the simulated testing results for the stock market trading heuristic, "Buy when one-day share volume spikes". The simulated testing applies the method ex ante to historical market data for two major indices, the Dow Jones Industrial Average and the Standard & Poor's 500 Index. Results summarize performance of the heuristic for entire time series, for six equally long folds for each time series, for an extension of the basic heuristic which uses correlation of past volume and price return values as a condition, and for a range of values of the parameters of the basic and extended heuristic methods. The main objective is to present the methods and the results in a straightforward, thorough, and convincing way so that practical and substantive significance (beyond any suspicion of "data dredging") is established, and the effectiveness of the trading heuristic, "Buy when one-day share volume spikes", is demonstrated thoroughly.

Five sections follow this short introduction: a literature review, titled "2. Background", followed by "3. Method", "4. Results", "5. The stock market as an information processing system", which explains the results in terms of the behavior of market participants, and "6. Conclusion".

2. Background

The stock market is a complex information processing system with major human elements. Price and volume are primary dimensional attributes of this system. Blume, Easley, and O'Hara (1994), Hiemstra and Jones (1994), and Mahesh and Singal (2001) appeared in journals of academic finance and investigate the relationship between volume and price, survey the prior literature, develop elaborate and sophisticated econometric models and rigorous statistical test procedures, and present empirical results. These are excellent research papers and exemplify the current efficient markets investigation paradigm of academic finance, which entails continuous econometrics models based on regression analysis and the use of complex statistical techniques to find and test relationships.

The fact that there is a relationship between share volume and price is well-established even though the nature

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of that relationship is still under investigation. Blume et al. (1994) summarizes, “This research has documented a remarkably strong relation between volume and the absolute value of price changes in both equity markets and futures markets. But why such a pattern exists or even how volume evolves in markets is not clear. ” Hiemstra and Jones (1994) observes, “After filtering the stock returns series with exponential generalized ARCH (EGARCH) models to control for volatility persistence, the modified Baek and Brock test continues to show evidence of significant nonlinear Granger causality from trading volume to stock returns in both sample periods.” Mahesh and Singal (2001) investigates the interaction of public announcements and share volume and finds, “Conditional on volume increases and public announcements, positive events are followed by a statistically significant abnormal return of 1.98% and negative events are followed by a statistically significant abnormal return of −1.68% over a 20-day period”.

The objectives of this paper are more modest than those of the three papers referenced above. We do not attempt to develop a comprehensive model of the stock market mechanism but only to develop methods to be used for decision support by stock market investors and speculators. We propose to demonstrate a computationally efficient and conceptually simple method for identifying volume spikes and show that the volume spikes identified can be used effectively as signals for buying opportunities over long periods for major market indices.

The method of this paper uses share volume to identify instances of future price increase, but does not attempt to forecast the magnitude of that increase. Blume et al. (1994), Hiemstra and Jones (1994), and Mahesh and Singal (2001) set out to forecast the magnitude of future price increase, using the statistical tools of econometrics. Predicting an instance of positive price change is a classification problem, but predicting the direction and magnitude of the price change is a parameter value estimation problem. Classification is a less rigorous requirement than value estimation. (see “Classification Is Easier Than Regression Function Estimation” in Devroye, Gyorfi, & Lugosi, 1991).

Leigh, Modani, and Hightower (2004) is more similar in method and objective to this paper than are the first three referenced papers (Blume et al., 1994; Hiemstra & Jones, 1994; Mahesh & Singal, 2001). Leigh et al. (2004) uses the volume spike as a heuristic buy signal or “filter rule”, like in this paper. Leigh et al. (2004) uses a pattern recognition technique to implement an approach to “stock charting” to recognize an upward spike in past volume which takes place over multiple trading days, and this is a more elaborate method that what is used to identify a single day spike in this paper. Leigh et al. (2004) conditions the use of that volume spike identification on past price change, rather than conditioning on correlation of volume and price, as is done in this paper. In effect, this paper reports a major simplification and refinement of the methods used in Leigh et al. (2004), tests on much longer series of data, and finds much stronger evidence supporting the validity of the basis of its methods. This paper isolates the core component of the method presented in Leigh et al. (2004), which is the identification of the most recent trading day volume spike.

This paper and Leigh et al. (2004) are of a different paradigm than Blume et al. (1994), Hiemstra and Jones (1994), and Mahesh and Singal (2001). Blume et al. (1994), Hiemstra and Jones (1994), and Mahesh and Singal (2001) exemplify the finance and econometrics approach to modeling the stock market mechanism. They use tools which were designed for continuous relationships and normal distributions, and which handle nonlinear relationships with some difficulty, and which have as their objective the forecasting of actual price values at future times (which is parameter value estimation). The real world of the stock market, like most real worlds, is discontinuous, nonlinear, and non-normal. The regression analysis tools of finance and econometrics must be used with great skill and complication to discern relationships in the nonlinear, discontinuous, and non-normal real world of the stock market. Rule-based and heuristic methods (as employed in this paper and in Leigh et al., 2004), which fit naturally classification problems rather than parameter value estimation problems, are directly applicable for detecting and representing the classification aspects of nonlinear and discontinuous relationships in a world of non-normal distributions. The objective in stock trading is sustained profit in excess of what is realized by the buy-and-hold strategy, so the forecasting of actual price levels is only of indirect interest. Forecasts of actual price values can be a basis for trading decisions, but a method which supplies only a buy/don’t-buy binary signal for each trading day is sufficient for decision support if it is effective in the realization of returns in excess of those from buy-and-hold.

Many, if not most or even all, of the stock market analysts on Wall Street practice, at least in part, “technical analysis”. Technical analysis uses the past dynamics of price and volume to predict future stock price. Edwards and Magee (1997) is a standard reference on technical analysis, though 1000s of other books have been written on technical analysis. Academic finance, in general, holds technical analysis in low repute – in fact, most interpretations of the efficient markets hypothesis, which is one of the theoretical pillars of academic finance, hold that technical analysis is nonsense. In the last few years academic finance has begun to acknowledge that there is some worth to technical analysis, at least to its concentration on price and volume dynamics, and this acknowledgement is exemplified notably by the publication of Blume et al. (1994), Hiemstra and Jones (1994), Mahesh and Singal (2001), Hong, Lim, and Stein (2000), Lo, Mamaysky, and Wang (2000) in prestigious journals of academic finance. However, the heuristic and rule-based methods of technical analytic practice are still considered by academic finance to be inappropriate for rigorous relationship identification and testing, though these heuristic and rule-based methods deal very well with the discontinuous, nonlinear, and non-normal reality of the stock markets. Instead, academic finance develops increasingly complex and difficult statistical methods to extend the regression-based methods of econometrics to handle relationships which are discontinuous and nonlinear and distributions which are non-normal.

For many years research on stock market timing has been impeded by strict interpretation of the efficient markets hypothesis, making efforts at market timing seem to be futile. However, as reports of exceptions to market efficiency, called "anomalies" (surveyed in Oguzsoy & Guven, 2007 and analyzed in Brav & Heaton, 2002), have become more numerous, academic finance may be gradually moving away from the idea that a strict efficient markets hypothesis is true and may be more open to the consideration of possible technical heuristics (even stock charting Lo et al., 2000) and analytic relationships which may be useful in the development of models of the stock market mechanism. In anticipation of eventual recognition of the worth of this work in academic finance and in the very real and now objective of making money trading stocks, researchers in management science and decision support systems can be identifying, defining, interpreting and clarifying relationships between volume and price to reduce them to practical terms so that they may be tested and exploited in actual trading applications. This paper is an example of an effort to do just that.

3. Method

We look at time series composed of trading data from stock market indices. The time series data is made up of data pairs, a price p_t and a share volume v_t, for each trading day t included in the time series. A return, $r_{h,t}$, which is based on a trading day horizon h, is computed as the change in the closing price at trading day t to a trading day h days in the future divided by the price at trading day t.

Hence we have:

$t = 1, \ldots, n$ index for n trading days;
$p_t =$ price closing value of index or security on trading day t;
$v_t =$ share volume of index on trading day t;
$h = 1, 2, 3, 4, 5, 10, 20, 40,$ or 80 number of trading days; between buying and selling, that is, the return horizon;
$r_{h,t} = (p_{t+h} - p_t)/p_t$ return over horizon h for trading day t.

A volume "spike" is identified for trading day t if the volume v_t exceeds a threshold value. The computation of the value for this threshold starts with the identification of a past volume set for v_t, which is a set of share volume values for 1000 trading days preceding day t in the time series. (We have not optimized the setting of 1000 days in the past volume set – this is a topic for future work.) Next the average and standard deviation are computed for the volume set. The threshold value is then computed as the sum of the average volume and the product of a "filter multiple" m and the standard deviation.

This gives for trading day t:

$V_t = \{v_k | t - 1000 \leqslant k \leqslant t - 1\}$ past volume set;
$a_t = 1/1000 \sum v_k$ the average volume for the past volume set V_t;
$s_t = \sqrt{[1/(1000-1)\sum(v_k - a_t)^2]}$ the standard deviation for the;
past volume set V_t;
$m = 0, 1, 2,$ or 3 a filter multiple.

Finally we have,

$$e_{m,t} = \begin{cases} 1, & \text{if } v_t > a_t + m \cdot s_t \text{ a volume exceeds threshold value} \\ 0, & \text{otherwise} \end{cases}$$

Next, we define two approaches to buying and selling of stocks. The *basic method* specifies that a "buy" be made on a trading day that is identified as a volume spike trading day. We call these days "buy days". Each investment is then held for the duration of the return horizon h and then sold. This implements a trading rule of the form: "If the volume on day t exceeds the volume threshold value for that day, then buy and hold for h trading days." Back-testing, or simulating trading, using this trading rule is performed and is evaluated using "excess profit", which is the difference between the average return realized for the rule-based trading and the over all average return for the interval (which is the return that would be realized by the buy-and-hold strategy).

For the basic method we have for a time interval of n trading days:
$n^B = \sum_{t=1}^{n} e_{m,t}$ the number of basic method buy days;
$\bar{r}^B = 1/n^B \sum_{t=1}^{n} (r_{h,t} \cdot e_{m,t})$ the average return for basic method trading;
$\bar{r} = 1/n \sum_{t=1}^{n} r_{h,t}$ the over all average return for the interval;$\Delta\bar{r}^B = \bar{r}^B - \bar{r}$ the average excess return for the interval for the basic method;
$P^B = 100 \cdot \Delta\bar{r}^B / |\bar{r}|$ the average excess return for the interval for the basic method as a percentage of the absolute value of the over all average return;

The *extended method* builds on the basic method by specifying that an additional condition must be met before buying on a given day. For this method, a "buy" is made on a trading day t if that day is identified as a volume spike trading day AND also meets a second filter condition defined by the correlation of five past return and volume values for day t. (We have done preliminary work in optimizing this parameter value setting of 5 days in the correlation set – more work is needed.) Price movement, and hence return, possesses a characteristic resembling physical inertia, called, as with physical movement, "momentum"

Hong et al. (2000), and this is the tendency of prices to continue in a direction, once started. This is a result of the mutually influencing mechanisms of information diffusion and psychological herding Sias and Richard (2004). The conjecture employed in the extended method is that if past upside volume changes preceded upside price movement, then the same is likely to be true for immediately following volume changes. The extended method uses a correlation of past 1-day volume and 1-day price movement to estimate the likelihood of the current volume spike being a signal for an upside price movement, that is, to estimate the direction of the momentum. This may detect the direction of sentiment in any public announcements which precede the volume spike.

A correlation coefficient is a measure of the degree of variability in one series that is explained by a second series and is implemented for two sets of values X and Y by the Microsoft EXCEL function as

$$\mathrm{correl}(X,Y) = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2\sum(y-\bar{y})^2}}$$

Let us define the correlation between a volume set and a return set for trading day t using five past daily volume and return values where:

$X_t = \{v_k | t-5-1 <= k <= t-1\}$ past volume set;
$Y_t = \{r_{1,k} | t-5-1 <= k <= t-1\}$ past return set with $h = 1$;

Note that the past volume and return sets X_t and Y_t are offset to the past by 1, the number of trading days in the return horizon of the past return set Y_t, so that there will be no look-ahead. Now let,

$C_t =$ correlation coefficient as computed from the sets X_t and Y_t of values paired as $(v_k, r_{1,k})$

Finally we have,

$$f_t = \begin{cases} 1, & \text{if } C_t > 0.1 \quad \text{a high correlation is identified} \\ 0, & \text{otherwise} \end{cases}$$

For this method, a "buy" is made on a trading day t if that day is identified as a volume spike trading day AND also meets a second filter condition defined by the correlation of five past return and volume values for day t. Values other than 0.1 for the correlation filter threshold were tested, and 0.1 was found to reveal adequately the effectiveness of the heuristics being tested. More work is needed here, especially to determine the relationship between this correlation threshold and the number of days of history in the correlation sets (5 is used in this paper for the number of days represented in the correlation sets.)

Hence, for the extended method we have for a time interval of n trading days:

$n^E = \sum_{t=1}^{n} e_{m,t} \cdot f_t$ the number of extended method buy days;
$\bar{r}^E = 1/n^E \sum_{t=1}^{n} (r_{\mathrm{h,t}} \cdot e_{\mathrm{m,t}} \cdot f_t)$ the average return for extended method trading;
$\bar{r} = 1/n \sum_{t=1}^{n} r_{h,t}$ the over all average return for the interval;
$\Delta\bar{r}^E = \bar{r}^E - \bar{r}$ the average excess return for the interval for the extended method;
$P^E = 100 \cdot \Delta\bar{r}^E / |\bar{r}|$ the average excess return for the interval for the extended method as a percentage of the absolute value of the over all average return;

4. Results

Fig. 1 is a model results table, that is, a key for reading the summary results tables which follow. The notation developed above appears in the areas of the model results table in Fig. 1 which will contain the actual numerical results in the actual results tables.

Tables 1 and 2 present over all summary results for the Dow Jones Industrial Average and the Standard and Poor's 500 Index, respectively. Excess profit is positive everywhere in the tables for the basic ("buy on volume spike") method results. Excess profit is positive in the tables for the extended ("buy on volume spike if 5 day correlation > 0.1") method for filter multiple values of 2 and 3 and is often of substantial magnitude. Excess profit is negative for filter multiple value of 1 for only one return horizon for

		Begin: date				**End: date**		Days:	n
	Trading Rule:	**Basic Method: Buy on Volume Spike**				**Extended Method: Buy on Volume Spike If 5 Day Correlation > 0.1**			
	Filter Multiple:	m	...	...	...	...	...	...	...
	Buy Days:	n^B	...	...	...	n^E	...	...	...
Return Horizon	Interval Average Profit	Average Excess Profit as Percentage of Interval Average Profit				Average Excess Profit as Percentage of Interval Average Profit			
h	$\bar{r}$	P^B	...	...	...	P^E	...	...	...

Fig. 1. Schema of results tables showing correspondence with notation used in explanation of method.

Table 1
Dow Jones industrial average DJIA results over all for basic and extended methods

DJIA	Begin: 1/9/1934; End: 8/29/05; Days: 18,000								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	12,558	6658	2361	607	4558	2324	786	208
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00030	35	92	187	155	121	172	456	486
2	0.00061	27	79	122	178	93	144	358	583
3	0.00092	22	60	100	163	74	108	278	436
4	0.00123	20	47	97	131	54	80	265	417
5	0.00154	20	42	77	120	45	62	205	333
10	0.00306	15	30	62	134	6	38	91	207
20	0.00609	12	29	53	130	22	38	57	150
40	0.01213	11	24	56	94	17	37	46	87
60	0.01829	10	18	39	64	14	23	25	52
80	0.02450	8	19	40	72	9	17	31	75

Table 2
Standard and Poor's 500 Index S&P500 results over all for basic and extended methods

S&P500	Begin: 1/5/1954; End: 9/2/05; Days: 13,008								
	Trading rule: Buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	10,609	5957	2119	533	3862	2075	714	196
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00034	30	78	150	125	70	131	380	538
2	0.00069	23	65	107	160	60	120	311	458
3	0.00103	18	49	98	155	52	89	238	345
4	0.00138	16	41	102	144	41	78	242	313
5	0.00172	16	37	84	141	28	61	197	265
10	0.00343	9	21	57	134	−11	23	54	163
20	0.00684	5	15	36	110	7	25	27	101
40	0.01362	5	9	37	77	8	27	40	64
60	0.02045	5	4	26	50	5	9	16	23
80	0.02735	4	6	25	56	2	6	18	59

S&P500. In general, performance of both the basic and extended methods improves as the filter multiple m is raised from 0 to 3. There is degradation in performance as the return horizon is increased for both methods with more pronounced degradation for the extended method than for the basic method. Excess profit results are generally higher for the extended method than for the basic method in cells for the higher filter multiple values and lower trading horizon values.

Tables 3 and 4 present results for the Dow Jones Industrial Average summarized by the six cross-validation folds. The basic method performs poorly in Fold 1 (1934–1946). The extended method has weak results in Fold 3 (1957–1970). Both methods perform very well in the most recent fold, Fold 6 (1993–2005).

Tables 5 and 6 present results for the Standard and Poor's 500 Index summarized by the six folds. The basic method performs poorly in Fold 5 (1988–1997). The basic method and the extended methods both perform well in the most recent fold, Fold 6 (1993–2005).

5. The stock market as an information processing system

"Good news" causes a price increase, and "bad news" causes a price decrease, and both good and bad news are accompanied by higher volumes because market participants apply varying estimations of the impact of the news (Mahesh & Singal, 2001). Information diffuses gradually and has varying effect on valuation through the population of investors, because investors have differing investment objectives and differing degrees of access to information and different levels of expertise, attention, and time with which to interpret that news and apply its import to their situation. Good news and bad news do not propagate symmetrically Hong et al. (2000). The executives of companies which have good news to report encourage and facilitate

Table 3
Dow Jones Industrial Average (DJIA) results by fold (first 3 folds)

DJIA	Begin: 1/9/1934; End: 1/8/46; Days: 3000								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 1	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	1060	354	113	31	335	93	32	12
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00030	54	40	485	1122	327	312	368	951
2	0.00060	14	−7	215	239	141	141	150	324
3	0.00090	22	−56	−20	5	147	74	6	304
4	0.00122	37	−61	−101	−179	130	28	−50	560
5	0.00152	47	−99	−98	−350	178	49	69	289
10	0.00298	49	−77	−164	−257	149	45	−65	46
20	0.00581	42	−8	−58	−69	103	36	−21	250
40	0.01127	22	35	66	28	64	67	91	178
60	0.01729	20	18	5	−63	34	30	−2	−15
80	0.02345	23	32	21	−39	26	14	0	−20
	Begin: 1/9/1946; End: 12/27/57; Days: 3000								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 2	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	1625	598	220	76	578	213	67	23
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00029	78	245	385	368	182	227	900	1023
2	0.00058	89	241	233	268	179	229	612	1 497
3	0.00087	67	167	78	66	128	78	208	796
4	0.00116	52	112	68	−46	107	44	264	607
5	0.00146	52	119	122	−49	94	60	277	422
10	0.00293	36	93	125	64	30	23	42	127
20	0.00590	38	108	180	171	78	86	211	189
40	0.01203	43	98	140	105	58	86	103	31
60	0.01817	45	106	115	93	68	117	91	74
80	0.02391	39	105	137	125	47	93	99	120
	Begin: 12/30/1957; End: 1/7/70; Days: 3000								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 3	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	2435	1327	510	132	876	456	165	45
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00023	68	182	153	65	−8	137	−86	−389
2	0.00046	57	167	196	221	24	95	57	−172
3	0.00068	50	141	142	248	18	114	74	266
4	0.00090	37	102	125	191	8	88	128	316
5	0.00112	32	88	89	215	−1	64	46	289
10	0.00223	23	32	−12	72	−31	−29	−163	63
20	0.00431	6	−6	−59	33	−24	−55	−190	7
40	0.00853	5	−7	20	43	−23	−40	−26	25
60	0.01288	5	6	14	15	−13	−32	−47	−55
80	0.01721	0	−2	−3	−20	−19	−52	−59	−74

the dissemination of the good news as do the stock brokers who want to bring new money into the stock market (as do the news media who are in the employ of the executives and stock brokers). These actors who widely broadcast the good news work in reverse to impede the dissemination of bad news. In addition the short-selling regulations and tax laws arrest and attenuate the price effect of bad news. These factors explain why (a) the impact of good news on price is rapid and pronounced relative to the impact of bad news which occurs gradually and is softened; therefore (b) one-day volume spikes are more likely to precede abrupt market upturns than they are to precede abrupt market downturns; and (c) information diffusion rates and feed-forward information mechanisms, such as

Table 4
Dow Jones Industrial Average DJIA results by fold (last 3 folds)

DJIA	Begin: 1/8/1970; End: 11/19/81; Days: 3000								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 4	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	2229	1112	414	125	744	315	106	31
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00006	238	652	1835	−1128	566	660	4684	1983
2	0.00014	186	239	812	839	608	455	2428	4241
3	0.00023	85	115	379	523	291	289	1335	2039
4	0.00032	75	47	342	596	170	2	1055	2026
5	0.00042	54	44	1 88	444	61	−133	606	1484
10	0.00088	−3	−33	116	295	35	58	169	664
20	0.00188	1	−9	30	226	89	54	−27	23
40	0.00376	−14	−74	−66	22	88	13	−183	−240
60	0.00527	−10	−66	−14	122	97	−21	−85	34
80	0.00677	−24	−44	68	263	69	8	50	323
DJIA	Begin: 11/20/1981; End: 10/1/93; Days: 3000								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 5	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	2411	1290	442	131	847	427	150	46
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00054	−3	10	27	65	4	27	112	511
2	0.00108	−21	1	−40	−62	−5	44	58	135
3	0.00161	−16	−10	8	34	1	22	117	168
4	0.00213	−10	−7	27	64	−13	−4	142	273
5	0.00265	−5	−2	14	23	−22	−19	87	174
10	0.00525	−5	−6	20	83	−27	−2	38	84
20	0.01053	−7	−7	16	63	−23	−18	−7	44
40	0.02133	−1	0	44	94	−11	−5	30	56
60	0.03252	−1	−3	23	69	−14	−5	16	43
80	0.04421	−1	0	19	68	−14	−9	24	73
DJIA	Begin: 10/4/1993; End: 8/29/05; Days: 3000								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 6	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	2798	1977	662	112	1178	820	266	51
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00041	2	23	66	275	148	172	442	357
2	0.00083	11	46	94	329	93	139	414	689
3	0.00123	12	52	1 28	304	83	116	344	440
4	0.00164	10	52	1 26	240	65	114	292	245
5	0.00205	6	44	1 06	306	61	100	249	285
10	0.00409	7	46	119	321	−4	57	192	348
20	0.00810	10	44	1 01	279	19	66	140	276
40	0.01585	5	31	59	147	8	52	59	163
60	0.02361	2	14	44	80	3	20	31	86
80	0.03143	1	13	39	84	5	20	30	79

momentum (Hong et al., 2000) and herding (Sias & Richard, 2004), ensure that the direction of the price change immediately preceding and accompanying the volume spike is continued for some future period.

The explanation above is consistent with the results of this study.

6. Conclusion

The basic version of the method presented herein implements a definition of volume spike and uses one-day volume spike as a filter to identify buying opportunities. The simulated trading results show that this method of

Table 5
Standard & Poor's 500 Index S&P500 results by fold (first 3 folds)

S&P500	Begin: 1/5/1954; End: 8/10/62; Days: 2168								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 1	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	1563	662	253	73	554	217	68	22
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00041	82	175	199	117	−25	121	225	602
2	0.00083	70	179	160	239	51	229	346	472
3	0.00126	61	151	138	120	72	198	269	458
4	0.00168	47	120	116	6	74	193	365	422
5	0.00211	42	89	95	−56	74	182	331	359
10	0.00427	30	62	48	−13	29	93	113	175
20	0.00841	25	55	63	63	35	64	92	66
40	0.01655	37	64	107	98	18	55	102	68
60	0.02447	39	72	88	83	19	67	86	59
80	0.03289	30	59	73	36	12	45	49	23
S&P500	Begin: 8/13/1962; End: 4/29/71; Days: 2168								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 2	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	1818	1045	415	111	646	356	145	40
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00029	27	152	292	270	73	305	488	390
2	0.00059	24	121	255	269	54	180	323	263
3	0.00088	18	89	173	244	12	114	207	166
4	0.00117	13	69	151	187	−5	72	204	54
5	0.00146	17	70	119	185	−14	43	157	36
10	0.00290	7	27	17	84	−71	−58	−53	−11
20	0.00570	−7	−20	−67	6	−66	−84	−178	−98
40	0.01150	−14	−25	−25	11	−38	−51	−44	−52
60	0.01746	−16	−25	−34	−24	−40	−80	−100	−113
80	0.02251	−14	−27	−53	−57	−33	−76	−82	−100
S&P500	Begin: 4/30/1971; End: 11/28/79; Days: 2168								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 3	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	1521	696	246	69	467	159	52	15
Return horizon	Interval average profit		Average excess profit as percentage of interval average profit (%)			Average excess profit as percentage of interval average profit (%)			
1	0.00005	422	623	1445	−3253	1519	1104	5658	2957
2	0.00012	337	338	289	−402	1034	746	2452	5332
3	0.00018	182	122	−45	285	664	193	387	2163
4	0.00025	153	−48	−55	596	522	−283	−284	1634
5	0.00032	129	−37	−144	403	319	−472	−540	1097
10	0.00065	31	−118	1	292	52	−425	−913	229
20	0.00150	24	11	201	652	182	30	71	731
40	0.00335	−3	−128	5	339	76	−201	−337	256
60	0.00558	15	−72	53	335	94	−118	−178	462
80	0.00761	11	−37	99	418	34	−99	−31	766

implementation of the trading heuristic, "buy on volume spike", is effective. The extended version of the method employs a variation of market momentum, computing the correlation of past return and volume, to better differentiate the one-day volume increases that precede price advances from those that precede price declines. Results of testing show that this correlation of past return with volume is an effective way of estimating the likelihood of a volume spike signaling future market rise and the use of this variation on market momentum as a filter applied after the application of the volume spike filter improves the performance of the basic method for shorter return horizons.

For the basic method all parameter value settings are reported and no optimization has occurred except for the

Table 6
Standard & Poor's 500 Index S&P500 results by fold (last 3 folds)

S&P500	Begin: 11/29/1979; End: 6/27/88; Days: 2168								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 4	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	2078	1245	447	137	697	408	143	49
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00050	9	−7	64	57	−29	−70	110	398
2	0.00100	0	−16	17	20	−28	−47	33	155
3	0.00150	0	−22	17	55	−14	−25	45	189
4	0.00200	2	−16	14	93	1	1	76	304
5	0.00249	2	−8	3	51	−29	7	34	1 86
10	0.00494	2	−13	11	106	−5	21	−13	78
20	0.00974	−3	−8	−3	44	1	13	−11	21
40	0.01923	−4	−4	14	45	15	23	37	5
60	0.02828	−4	−11	3	36	7	4	10	9
80	0.03814	−4	−5	14	60	−1	1	24	58
S&P500	Begin: 6/28/1988; End: 1/22/97; Days: 2168								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 5	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	1621	923	295	54	628	335	112	27
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00051	−12	29	22	−55	63	138	255	504
2	0.00102	−21	6	−14	−108	30	69	220	364
3	0.00153	−16	1	28	25	21	39	174	305
4	0.00203	−11	7	65	45	19	52	214	250
5	0.00254	−3	7	52	69	29	46	192	221
10	0.00512	−7	−5	−1	−18	10	33	78	81
20	0.01043	−7	−7	3	48	10	18	50	139
40	0.02116	1	−3	0	−19	10	14	15	27
60	0.03159	0	−6	−15	−44	13	17	9	2
80	0.04242	1	−4	−10	−33	8	8	−1	−17
S&P500	Begin: 1/23/1997; End: 9/2/05; Days: 2168								
	Trading rule: buy on volume spike					Buy on volume spike if 5 day correlation > 0.1			
Fold 6	Filter multiple:	0	1	2	3	0	1	2	3
	Buy days:	2008	1386	463	89	870	600	194	43
Return horizon	Interval average profit	Average excess profit as percentage of interval average profit (%)				Average excess profit as percentage of interval average profit (%)			
1	0.00029	5	66	114	730	140	165	494	541
2	0.00057	15	85	173	628	105	194	529	773
3	0.00086	15	82	202	420	108	158	476	481
4	0.00114	10	80	226	378	54	123	406	308
5	0.00143	7	67	221	554	40	85	355	416
10	0.00272	9	76	241	571	−60	32	205	494
20	0.00524	14	66	187	429	3	74	158	317
40	0.00993	5	48	126	268	2	87	126	288
60	0.01533	−2	18	115	169	−12	30	94	99
80	0.02055	−2	20	100	216	−3	36	83	210

1000 day length of the history period. For the extended method, some optimization of the size of the correlation sets and the correlation threshold value have occurred previous to the presentation of the results, and the preliminary results from that optimization are not included in this paper. Presentation of results from the investigation of multiple settings for these three additional parameters would make this paper of prohibitive length. The primary objective of this paper is to present the methods and the results in a straightforward, thorough, and convincing way so that substantive significance is established, and we believe that that has been accomplished by the presentation of the results included and that there is no need for an exhaustive presentation of results from processing with all combinations of parameter value settings.

Several attributes of this work combine to make a strong case that the volume spike heuristic cannot be considered ‘‘anomalous’’ but reflects a very real phenomenon in the stock markets that should be explained by any theories of how the stock markets function:

(1) conceptual and computational simplicity of the basic and extended methods;
(2) strong and systematic simulated trading performance results;
(3) testing with very long time series on two major indices for several values of the parameters of the method;
(4) cross-validation testing with 6 folds, for a total of 12 folds for the 2 stock indexes, with positive results for 10 of the 12 folds for the basic method and for 11 of the 12 folds for the extended method;
(5) both basic and extended methods perform very well in the most recent fold;
(6) methods and results are consistent with research reported in academic finance literature.

The methods are straightforward and are readily implemented with spreadsheet technology for decision support applications. Testing shows that the methods work for historical and current stock market time series data. The methods should be considered for inclusion as elements of any market trading decision support system, although of themselves as limited opportunistic heuristics they do not constitute a complete investment strategy.

The trading heuristic, ‘‘Buy when one-day share volume spikes’’, is demonstrated to be effective for simulated trading with long time series market data for major stock indices.

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