The Day Trader: Some Additional Evidence

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I. Introduction

The question of stock market efficiency has received considerable play in the financial press in recent years and understandably so. Not only is this a topic of interest to national policymakers charged with monitoring and promoting market efficiency, but answers to this question have rather important implications for the management of market participants' portfolios. Our interest in this subject focuses on a subsegment of the larger question of market efficiency, in particular on so-called technical theories of stock market behavior.

There is, of course, an almost endless variety of "technical indicator" theories and associated tests of those theories that can be performed over many different stock market periods. Our investigation examines market portfolio indicators during the period 1972 through 1975 and concentrates on very short-term forecasts and speculative strategies. The study is thus a limited one; but does give us a fresh look at the performance of a hypothetical day-trader during a recent and interesting period of stock market history. The speculator is generally unsuccessful at beating the market, but the results do contain some interesting information on sensitivity to filter size, assumed transactions, frequency of trading, and the possibility of certain groups of speculators outperforming the market.

A legitimate question at this point is why perform another study of this nature. Part of the answer is that we find conflicting estimates of technical indicator value as we examine some of the previous studies in the area. For example, Kaish [17] and Crouch [4] examined odd-lot and volume indicators (respectively) and concluded that these series had some predictive value. Comparable research by Kewley and Stevenson [19] and Osborne [27] came to the opposite conclusions. Investigations by Freeman [10] and by Philippatos and Nawrocki [29] suggested that advance-decline information could be useful in estimating stock prices, evidence not at all in keeping with the findings of Zakon and

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Pennypacker [34]. Other studies, those performed by Seneca [32], Mayor [21], McDonald and Baron [22], and Kerrigan [18] on short-interest figures, generally support the theories of market efficiency although the evidence across their work is not entirely consistent. James' 1968 study on moving averages of market indicators lends support to the efficient market hypothesis [14], but we find later pieces like Gup's 1973 investigation which suggest that certain types of moving averages can be useful in forecasting market changes [13].

Another rationale for this study is that recent and broader-based studies of technical indicators and market efficiency give us somewhat incomplete results. Emery reported the findings of a study covering the period October 1965 through March 1972, in which he used eight technical indicators to describe overall market activity on the New York Stock Exchange [5]. He found some predictive power in the indicators, but uncovered no superior net profit possibilities using a simple 1 percent daily trading filter. Another study, that by Branch [2], covered a considerably longer period (1960 through 1974) and investigated a more extensive list of possible technical indicators, but stopped short of actually testing competing investment strategies. There does seem to be room for additional investigation of technical indicator value in a simulated competitive environment allowing for more complex trading schemes.

The next section of the paper discusses the technical indicator forecasting model developed in our study and Section III reports the results of a number of trading strategies employed by our day-trader during the 1972 through 1975 period. A summary of the findings and some final observations on technical indicator models appear in the last section.

II. The Technical Indicator Model and Market Forecasts

The speculator in this study was presumed to be interested in outperforming the "market portfolio" through the use of daily stock market forecasts generated from an aggregate technical indicator model. While various groups of indicators have been suggested as being linked to market movements, four were chosen for this paper: advance and decline information, odd-lot figures, trading volume, and new highs and lows data. The New York Stock Exchange was chosen as the target market portfolio and daily data on the following raw series were thus collected: the DJIA index, the NYSE industrial index, new highs for the year, new lows for the year, the number of stocks advancing, the number of stocks declining, the total volume of odd-lot purchases, and the volume of odd-lot short-sales. While this was not an exhaustive list of "technical indicators," it did represent a broad spectrum of traditional leading market signals and was therefore deemed appropriate for the test comparisons in this study. All of the above series were market-closing figures recorded from the *Wall Street Journal* for the period January 3, 1972 through September 25, 1975, a period of 943 trading days.

Development of the model required the selection of a forecasting technique and the specification of the functional forms of the variables to be used in the model. Here we chose a multiple linear regression estimator, although there was no reason to believe that other techniques could not have been used with equal success.[1] As for variable forms, the daily change in the level of the NYSE index was chosen as the dependent variable after simple correlation analysis suggested its superiority over that of changes in the DJIA index.[2] The selection of the best predictor or independent variables required a bit more exploration.

The day-trader could choose from eight raw indicator series, a number of algebraic transformations of these indicators, and a wide range of possible forecasting lags. In an effort to pare this search down to a manageable size, a number of technical indicator ratios, differences, and 20-day moving averages were created. Each of these series was then lagged from 1 through 20 days[3] and subsequently correlated with the change in the market over the first 100 days of the period.[4] The results of this process, somewhat at odds with the findings of earlier studies [14, 19, 34], indicated that all moving average versions of the variables showed some predictive power and offered consistently better results than their raw series counterparts. In light of this, all versions except the moving average series were dropped from further analysis leaving the following six technical indicator variables:

MVOL = 20-day moving average of total market volume

MHILO = 20-day moving average of highs minus lows

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[1] Emery [5] for example used cluster techniques and principal components analysis.

[2] Change in, rather than level of, the market was suggested as a better form for the dependent variable by the referee, although the trading results were almost identical using either form.

[3] Prior investigations of market information lags indicate that the securities markets absorb new information within a relatively short period of time after its public dissemination (see, for example, [9] and [28]). A period of four full trading weeks was deemed a sufficiently long absorption period for this study. Selected indicators were tested for longer periods with no measurable improvement in forecasting power.

[4] This and subsequent steps in the development of the model were aided by the helpful comments of the referee.

MADEC = 20-day moving average of advances minus declines

MOLSP = 20-day moving average of odd-lot sales/odd-lot purchases

MSSTS = 20-day moving average of odd-lot shortsales/odd-lot sales

MSVOL - 20-day moving average of odd-lot sales/total volume

The correlation coefficients of these series with the NYSE-index change appear in Table 1. We can see that the 20-day lagging period seems to capture most of the information not yet embodied in market prices since all series' predictive power first rises and then declines. The five best lags for each indicator are boxed in the Table. Further, as suggested by standard technical theory, the volume (MVOL), hi-lo (MHILO), and advance-decline (MADEC) indicators seem to be leading positive signals of changes in market direction and the notion that the "odd-lot short-seller is always wrong" is supported in the generally negative relationship of the MSSTS variable. Somewhat surprisingly, the MOLSP variable has a positive sign indicating that small investors, at least those who do not engage in short-selling, may *not* in the aggregate misjudge the direction of market movements. The MSVOL variable (given the MVOL variable sign) seems to confirm this although in a weaker fashion. The sign reversals in the MADEC, MSSTS, and MSVOL variables are difficult to explain, although we do note that the signs are as expected in the more significant versions of the variable lags. Overall the results shown in Table 1 were sufficiently interesting to warrant further investigation of these indicators as candidates for possible inclusion in a technical indicator forecasting model.

The next step in the development of the model was the determination of which forms of the moving average indicators would be likely to produce the best forecasting results. This process was initially simplified by excluding all but the five best lagged versions of each of the six above indicator series.[5] The remaining 30 possible variables were then introduced into a stepwise regression program with the minimum t-value to enter set at 1.60. The model's results for the first 100 days of the sample data[6] are shown in Table 2 where we see that eight variables enter the regression. All of the series are represented at least once, with the two double representations occurring in the MHILO and MOLSP

[5]The critical values of the correlation coefficient for the variables are: 1%--.2291 5%--.1639 10%--.1282. All variables except the MSVOL series thus pass at least a .10 significance test. This last series was included as a possible regression variable since it was close to a .10 test level and because it could be eliminated in the regression estimation if it contributed nothing to the model.

[6]Of the original 943-day data set, 40 days had been lost due to the creation of the moving averages and the 20-day lags. The 100 days used here were the first 100 out of the remaining 903 in the sample.

TABLE 1

CORRELATION COEFFICIENTS OF LAGGED TECHNICAL INDICATORS WITH CHANGES IN THE NYSE INDEX

No. of Days Lag (1-20)	MVOL	MHILO	MADEC	MOLSP	MSSTS	MSVOL
0	.00204	-.02470	-.14854	.04604	.17782	-.04693
1	.00977	-.01566	-.19145	.05704	.13654	-.02911
2	.02954	-.00183	-.18098	.06121	.09504	-.04061
3	.05102	.01455	-.15798	.06327	.05837	-.04585
4	.07959	.03053	-.13616	.07859	.03427	-.07267
5	.10857	.04793	-.14081	.10285	.00019	-.03659
6	.12601	.06816	-.13219	.11609	-.04838	-.00217
7	.14676	.09557	-.09104	.12588	-.11234	.01309
8	.16914	.12171	-.02682	.12554	-.16483	.01032
9	.19434	.14007	.00653	.13872	-.20760	-.00838
10	.21359	.15748	.03793	.14602	-.25390	.00272
11	.22522	.17190	.08794	.14270	-.27046	.01274
12	.22260	.18171	.12658	.13725	-.27538	.04946
13	.21501	.18842	.17423	.12180	-.27563	.05408
14	.21056	.18966	.20906	.10253	-.25464	.04162
15	.19450	.18535	.22362	.08930	-.23657	.04552
16	.15995	.17612	.23224	.08139	-.20610	08217
17	.13258	.16723	.25490	.06398	-.17134	.11399
18	.11876	.14903	.26104	.04567	-.12371	.11167
19	.10132	.13102	.24515	.01393	-.08369	.11065
20	.08292	.10864	.22169	-.01986	-.03309	.10012

TABLE 2

TECHNICAL INDICATOR MODEL RESULTS

Variable	Regr. Coefficient	Std. Error	t Value		
$MVOL_{11}$	.49400	.12808	3.857		
$MHILO_{16}$	-.00970	.00284	3.421	R^2	= .27086
$MADEC_{18}$	.00225	.00070	3.208		
$MHILO_{12}$	-.00884	.00403	2.191	R^2_{cor}	= .20676
$MSSTS_{13}$	-134.08400	66.07936	2.029		
$MOLSP_{10}$	3.55116	2.10893	1.684	SEE	= .31841
$MSVOL_{16}$	.12201	.07543	1.617		
$MOLSP_{8}$	-3.02835	1.89513	1.598	F	= 4.2256
Constant	-4.33845	2.45402	1.768		

variables (which probably accounts for the perversity of the signs in these two series). While the R^2 is not particularly high, the equation is statistically significant and represents the best overall predictor among those examined in the study.

In regard to the number of observations to be included in the forecasting model, we found the regression parameters to be quite insensitive to this factor.[7] We chose 30-day regression estimators in an effort to preserve as much of the remaining test data as possible for use in the actual trading strategies. Each day's change in the NYSE index was then iteratively forecast using this aggregate model and the forecasts formed the basis for the filter rules developed in the next section.

III. Trading Rules and Results

The ultimate test of a market forecasting model is whether it can be used to outperform some alternative approach and here we assumed the day-trader was pitting the technical indicator forecasts against a Buy-and-Hold (B & H) strategy. Determination of superior performance in this context should realistically include not just changes in the market, but *all* costs and returns inherent in the two strategies. The active trader, for example, incurs higher information and transactions costs, is probably subject to higher tax rates due to the short-term nature of the strategy, and is likely to receive smaller total dividend payments than the B & H approach over any period of time. On the other hand, it is likely that the trader receives some positive returns on non-cash holdings when out of the market that tend to offset these factors. Precise treatment of these and similar trading phenomena becomes quite complex as well as unique to individual traders' preferences and time frames over which the strategies are compared. We have therefore made some simplifying assumptions for the filter tests in our study, namely:

1. Neither the B & H portfolio nor the day-trader receives dividends; and the latter moves to a perfectly liquid position when out of the market.
2. There is no differential tax treatment of gains or losses for the two strategies.
3. There are no (or equivalent) information-gathering or processing costs for the two approaches.
4. The risk level of the two approaches is identical.
5. Commission fees are assumed to be an average of 1 percent of the transaction price (for both buy and sell orders).

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[7] These results are in keeping with Emery's [5] findings.

Before we look at the filter results, it is appropriate to speculate on the effect these assumptions may have on our ability to draw valid comparisons of the two approaches. Assumption 1 dealing with dividend and non-market portfolio returns is clearly unrealistic but may do little harm to relative performance measurement. If for example the trader purchased a portfolio of Treasury Bills (or other low-risk investments) when out of the market, it may be that over reasonable periods of time the marginal Bill yield received by this portfolio would approximate the dividend yield being received on the B & H portfolio. In this case and given the fact that both types of returns receive equal tax treatment, no important penalty for either strategy would occur.

Taking Assumptions 2 and 3 together, it is apparent that the day-trader would be at some disadvantage. Some costs, those associated with changes in the "market portfolio" necessitated by changes in exchange listings and the like, should be about the same for both strategies. But the active trader will incur costs associated with gathering, coding, and processing the technical indicator data which are not applicable to the B & H portfolio. As for taxes, it is likely that most gains made by the active strategy would be taxed at ordinary income tax rates and that a substantial portion of B & H gains would be eligible for the lower capital gains tax treatment, although recent changes in the tax code might reduce this benefit somewhat for the B & H portfolio. Overall the combination of higher processing costs and taxes would put the trader at some comparative disadvantage, that disadvantage being smaller for larger portfolios with less frequent trading schemes.

Against these last two factors we must examine the actual risk exposure of the two strategies (Assumption 4). The riskiness of the speculative strategy would probably be lower than that of the B & H approach since the day-trader is assumed to move to a zero or very low risk position some of the time. Whether the lower risk exposure of the trader would exactly offset the higher processing and tax costs if problematical, but it may be that direct comparison of the results of the two strategies is not seriously biased even without explicit treatment of taxes, risk differentials, and fixed trading costs.

The issue of differential risk brings up a related problem: the ability to test for statistically significant differences in competing investment strategies where one approach does not involve active trading. This question is a difficult one to deal with whether using wealth changes or rate of return comparisons. Praetz [30, 31] and Stevenson and Bear [33] grapple with this problem, but offer no solution to the dilemma, a dilemma which remains unresolved in our study as well. The problem does deserve additional attention, however, inasmuch as it remains a major area of contention in interpreting the results of such market efficiency tests.

The last assumption we make in our comparisons has to do with commission fees charged for trading activities. The figure of 1 percent of the transaction price is a rather standard assumption in filter tests, but may understate actual trading costs especially for smaller investors. Both price spreads and broker's fees are included in the 1 percent assumption, and this is undoubtedly lower than the full transactions costs for many market participants. We will re-examine the level of commission fees later in the paper.

Within this admittedly simplified framework, three different but related filter rules were created for use by our day-trader. We assumed that the day-trader was interested in maximizing accumulated profits, i.e., the performance standard for the two strategies would be net changes in wealth position over the period. We further assumed some knowledge on the part of the trader of possible ranges of daily changes in the stock market and thus cast the filters as follows:

FILTER ONE:

Buy the market portfolio if the projected daily increase is $\geq$ x%

Sell the market portfolio if the projected daily decrease is $\geq$ x%

FILTER TWO:

Buy the market portfolio if the projected daily increase is $\geq$ x% or if the projected change is $\geq$ y% below the last actual sell price on an accumulated basis.

Sell the market portfolio if the projected daily decrease is $\geq$ x% or if the projected change is $\geq$ y% above the last actual buy price on an accumulated basis.

FILTER THREE:

Buy the market portfolio if the projected change is $\geq$ y% below the last actual sell price on an accumulated basis.

Sell the market portfolio if the projected change is $\geq$ y% above the last actual buy price on an accumulated basis.

where the following conditions were imposed on all three filters:

1. $.10 \leq |x| \leq 1.50$, and varies in .10 increments.
2. $1.00 \leq |y| \leq 6.00$, and varies in .50 increments.
3. Orders are placed at the market opening which is assumed to be identical to the previous day's closing price, the market portfolio price for the filters.

Here one could argue that it is unnecessary to test filters which cause trades resulting in wealth changes that are less than the commission fees. This is true on a net profits basis but we will be examining the two strategies on both a gross *and* a net profits standard and therefore include "x" filter sizes that are less than the 1 percent fees to test for sensitivity to this variable. The assumption regarding the placement of orders was imposed solely to simplify the comparisons. In reality traders who have knowledge of any systematic bias in market movements during the day or between the evening's closing and the following day's opening may be able to improve their performance over that which will result here. Finally the reader will note that none of the filters contains a short-selling feature, largely in an effort to simplify the tests, but also because this feature will tend, on average, to simply double the strategy's gross profits, trading costs, and net profits. The probable effects of adding such a rule to the active strategy will be discussed after we examine the results of the simpler (and in all likelihood less costly) filters.

The day-trader's and B & H's trading results for Filters 1 and 2 appear in Table 3. We see there that using a Filter 1 approach (a simple buy-and-sell rule), the active trader could have outperformed the B & H portfolio on a gross profits basis but could not have achieved superior returns after the 1 percent assumed commission fees were deducted from the profits. Transactions costs were an important barrier for the active strategy causing Filter 1 to be a consistently poorer performer during the period covered by this study. Quite similar results were achieved with Filter 2, a combined daily and accumulated rule that simulated 154 different filter size combinations. The 5.00 percent accumulated filter results shown in the Table represent the most successful overall filter combinations, although above the level of 4.50 percent there was little if any change in the trader's performance. The larger accumulation feature slowed trading activity down, caused commission fees to decline and net profits to increase, but none of the filters tested here was able to beat the B & H approach.

Filter 3, a straight accumulated trading rule, gives us somewhat different results than those of the first two rules. Table 4 contains the profit figures for the day-trader and the B & H approach and we see there that most filter sizes outperformed the market portfolio: all filters beat the market on a gross basis, and 9 out of 11 filters outperformed the B & H strategy after commission fees. This was an important finding and led us to examine Filter 3 in more detail.

One of the questions that might be asked of the above results is "are they sensitive to market trends?" While we had no additional data over which to test Filter 3, we were able to split the original full data set into rising and falling market sub-periods as a partial answer to this question. While a trader would not have prior knowledge of these market turning points (any more than the B & H investor would), this information would be helpful to us in assessing the reliability of a Filter 3 approach. The outcome of the sub-periods tests for Filter 3 indicated that the active trader would have outperformed the market on a net profits basis only during bear market trends and would have been a consistently poorer performer (after commission fees) when the market was generally

TABLE 3

RESULTS OF FILTER 1 AND FILTER 2 VS. BUY & HOLD STRATEGY*

FILTER 1					FILTER 2				
Fil. Size	No. Trans.	Gross Profits	Total Comm.	Net Profits	Fil. Size	No. Trans.	Gross Profits	Total Comm.	Net Profits
.10	363	$ 56.95	$204.21	$-147.26	.10	360	$ 57.04	$202.90	$-145.86
.20	349	52.59	196.38	-143.79	.20	351	54.61	197.28	-142.67
.30	329	52.11	183.66	-131.55	.30	331	55.67	184.57	-128.90
.40	315	50.26	175.27	-125.01	.40	319	52.62	177.23	-124.61
.50	293	50.33	162.36	-112.03	.50	297	53.53	164.32	-110.79
.60	285	47.40	158.03	-110.63	.60	289	51.91	159.98	-108.07
.70	261	53.24	143.27	- 90.03	.70	267	57.67	146.21	- 88.54
.80	249	54.42	136.33	- 81.91	.80	257	58.49	140.14	- 81.65
.90	239	52.41	130.46	- 78.05	.90	247	56.50	134.26	- 77.76
1.00	225	47.87	122.09	- 74.22	1.00	233	54.11	125.91	- 71.80
1.10	194	49.03	103.90	- 54.86	1.10	206	55.25	109.95	- 54.70
1.20	180	47.53	95.97	- 48.44	1.20	188	57.57	99.71	- 42.14
1.30	172	43.38	91.06	- 47.68	1.30	182	52.62	96.08	- 43.46
1.40	168	37.61	89.27	- 51.66	1.40	178	47.71	94.29	- 46.58
1.50	156	36.51	82.51	- 46.00	1.50	168	47.84	88.67	- 40.83
B & H	1	-16.01	.67	- 16.68	B & H	1	-16.01	.67	- 16.68

*Filter 2 figures are for the 5.00% accumulated series; other Filter 2 results available on request. Filter sizes are in percentages. The initial portfolio investment was $67.01.

TABLE 4

RESULTS OF FILTER 3 VS. BUY AND HOLD STRATEGY*

Fil. Size	No. Trans.	Gross Profits	Total Comm.	Net Profits
1.00	23	$- 7.10	$15.09	$-22.19
1.50	17	- 7.77	11.18	-18.95
2.00	17	- 3.45	11.08	-14.53
2.50	11	- 6.74	7.26	-14.00
3.00	9	- 7.93	5.96	-13.89
3.50	9	- 6.64	5.95	-12.59
4.00	7	- 8.26	4.62	-12.88
4.50	7	- 6.42	4.55	-10.97
5.00	5	- 5.94	3.22	- 9.17
5.50	7	- 2.35	4.54	- 6.89
6.00	3	- 9.43	1.95	-11.38
B & H	1	-16.01	.67	-16.68

*Filter sizes are in percentages.

rising. Assuming equal knowledge of market direction in general (or more precisely, the lack of such knowledge) on the part of the trader and the B & H person, it is unlikely that this filter could consistently beat the market over full market cycles. In fact, with no knowledge of market turning points and given the upward drift of the market over the very long haul, it is probable that this filter would lead to long-run poorer performance than a simple B & H approach after commission costs. Indeed, none of the various speculative strategies tested here would have been successful given the 1 percent commission fees assumed thus far in the study.

Because all of the results of the three filters suggested that the size of transactions costs was vitally important to the success of the day-trader's activities, we decided to pursue this issue a bit further. In particular, we calculated "breakeven commission fees" for the three filter rules where the breakeven fee was defined as that at which each size filter would have just allowed the day-trader to achieve the B & H level of profits *after* such fees. The breakeven fee indicates the maximum commission fee plus price spread that could have prevailed and still allowed the trader to break even on the generally higher cost active approach. If trading costs had been below these levels, the trader could have "beaten the market" on a net profits basis. The breakeven level of fees for this period is shown in Table 5.

TABLE 5

BREAKEVEN COMMISSION FEES FOR FILTERS VS. B & H*

Fil. Size	Filter One	Filter Two	Fil. Size	Filter Three
.10	.358	.361		
.20	.351	.359		
.30	.372	.390	1.00	.618
.40	.380	.389	1.50	.784
.50	.410	.425	2.00	1.207
.60	.403	.426	2.50	1.407
.70	.486	.506	3.00	1.527
.80	.519	.534	3.50	1.775
.90	.527	.543	4.00	1.962
1.00	.526	.560	4.50	2.472
1.10	.630	.652	5.00	3.949
1.20	.667	.743	5.50	3.530
1.30	.657	.719	6.00	5.141
1.40	.605	.681		
1.50	.642	.726		

*Filter sizes and commission fees are in percentages.

Examination of the table suggests that Filters 1 and 2 would have performed better using filter sizes in the intermediate to high range of those tested where the maximum fees ranged around .60 percent to .70 percent of the trading price. While it is not likely that such fee levels could have been achieved by any major subset of the investing public, it is possible that some groups of market participants (specialists, floor traders, etc.) could have operated below these ceilings. The breakeven fees for Filter 3 were quite high, indicating that substantial portions of the investment community could have possibly outperformed the market during this period and using a technical indicator model--again except for the fact that the success of Filter 3 would have required knowledge of the market trend.

IV. Summary and Conclusions

This paper pits a hypothetical day-trader against the vagaries of daily changes in stock prices on the New York Stock Exchange and finds that the trader's performance falls short of a B & H approach when reasonable commission fees are assessed on the trader's activities. The investigation examines a rather traditional array of market indicators, covers a rather short period of time, searches only for short-term trading profits, and simplifies cost/return phenomena for the two strategies--all of which limit the nature of the conclusions which can be made about technical trading schemes. The fact remains that during this time period and within these constraints, no combination of technical indicators and filter rules seemed capable of consistently "beating the market." The ability to short sell the market portfolio would not have altered this conclusion.

The study does reveal that there appeared to be some market inefficiencies during the 1972 through 1975 period, but the magnitude or "band" of these inefficiencies was so small as to eliminate profitable trading opportunities for most of the investment community. This finding is congruent with the conclusions of a number of similar, earlier studies. It is clear, however, that attempts to reduce trading costs have a solid economic foundation and the recent growth of third and fourth securities markets takes on undeniable logic against this backdrop. It is there that we might expect to find above-average profit portfolios.

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