IS TECHNICAL ANALYSIS PROFITABLE ON U.S. STOCKS WITH CERTAIN SIZE, LIQUIDITY OR INDUSTRY CHARACTERISTICS?

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Abstract

We consider whether popular moving average and trading range breakout technical trading rules are profitable on a subset of U.S. stocks with certain size, liquidity, and industry characteristics. We find these rules are rarely profitable during the period 1990 to 2004, however there is some evidence they are more profitable for smaller, less liquid stocks. There is no evidence of any industry bias in applying these rules and when a rule does produce statistically significant profits on a stock, these profits tend to be greater for longer decision period rules.

JEL classification: G14

Keywords: Technical trading rules, Size, Liquidity

Technical analysis continues to prove very popular with practitioners despite the majority of academic studies finding it does not produce profits that are large enough to compensate for the transaction costs incurred. We contribute to the literature by considering the profitability of popular trading rules on individual NYSE and NASDAQ stocks. This enables us to determine whether technical analysis is profitable on a small subset of stocks with certain characteristics even though it is not profitable across all stocks.

Since the first study on the profitability of technical trading rules on stocks by Fama and Blume (1966), there has been a large amount of interest in the profitability of trading rules. Most equity market studies have focused on the rules as they apply to major market indices. In a seminal piece, Brock, Lakonishok, and LeBaron (1992) find popular moving average and trading range break-out rules out-perform a buy-and-hold approach on the Dow Jones Industrial Average Index before transactions costs are accounted for. However, Bessembinder and Chan (1998) show these rules are not profitable after transaction costs.

The majority of international equity market evidence has considered the same moving average and trading range break-out rules and found similar results to the Brock et al. (1992) study. Hudson, Dempsey and Keasey (1996) test the Footsie 30 index, Detry and Gregoire (2001) test European indices, Bessembinder and Chan (1995) test Hong Kong and Japanese indices, and Parisi and Vasquez (2000) test Chilean indices. Each of these studies find the returns to technical analysis do not offset the costs incurred in the frequent trading required to implement the system.

Interestingly, practitioners continue to rely on technical trading systems despite the evidence they do not add value. Bray (2002) estimates automated trading systems generate 35% of all volume on the NYSE, while Talley (2002) suggests technical analysis may be becoming more popular as investors begin to question the accuracy of the accounting data that underpins fundamental analysis.

We investigate whether the mismatch between the academic literature and practitioner behavior stems from the samples used in previous academic studies, as there are several reasons why technical analysis may have no value on the actively traded stocks that constitute market indices, but be profitable on smaller, less liquid stocks. There is less incentive for analysts to cover smaller stocks (Bushman, Piotroski and Smith (2004)) and there is substantial evidence (Jegadeesh (2004)) that analyst's forecasts help inform the market about a company's prospects and keep the stock price efficient. The lack of analyst coverage of smaller stocks raises the possibility that the price of these stocks react to information more slowly resulting in trends that can be successfully captured by technical trading rules. This is consistent with the empirical evidence in the closely related momentum literature. Lesmond, Schill, and Zhou (2004) find momentum trading strategies perform better on small, less liquid stocks.

We also consider whether technical trading rules are more profitable when applied to stocks of certain industries. Fong and Yong (2004) find moving average rules are not profitable when applied to technology stocks due to their high volatility, but it is possible stocks in other industries have characteristics that are profitably captured by technical trading rules.

It is possible behavioral biases which are inherent in the decision making process for investors (Hirshleifer (2001)) leads to investors continuing to favor technical analysis because the profits on a small subset are so large that they offset the losses incurred in most trades. We investigate this by studying the economic significance, as measured by the level of transaction costs that would remove profit from the stocks where statistically significant profit is generated.

Our choice of individual NYSE and NASDAQ stock data over indices has several other advantages. Firstly, it has not been possible to trade most stock market indices in their own right until very recently. This would make it very costly to track such an index closely and thus calls into question the economic reality of papers based on index data. Secondly, indices are affected by a non-synchronous trading problem. Day and Wang (2002) show the infrequent trading of the component stocks of the Dow Jones Industrial Average can upwardly bias the results attributed to technical analysis on this index. Individual stocks do not suffer from this problem.

A small number of papers have considered technical trading rules on individual stocks, but they do not focus on differences in rule profitability across stocks with different size, liquidity, and industry characteristics. Corrado and Lee (1992) consider the profitability of filter rules on large (120 Dow Jones and S&P 100 stocks) over the period 1963-1989. Lo, Mamaysky and Wang (2000) examine the return characteristics of a range of technical analysis patterns for 50 CRSP stocks over the period 1962-1996. However, the do not consider the profitability of these patterns for stocks in general or stocks with different characteristics. More recently, Marshall, Young, and Rose (2006) consider the profitability of candlestick technical trading strategies on individual stocks, but they too focus on large stocks (30 DJIA component stocks).

We examine all stocks listed on the NYSE and NASDAQ exchanges that are present over the entire period 1990 to 2004 inclusive that have sufficient trading activity to be of interest to technical traders. A total of 866 stocks listed on the NYSE and 199 stocks listed on the NASDAQ qualified for inclusion in this study. We limit our core analysis to stocks that are present at the beginning and end of our sample period to aid our comparison of stocks with different characteristics and reduce the computational issues that arise from implementing our methodology on such a large data set.

It is unlikely survivorship bias is introduced to this study as the technical trading rules are very short-term with an average holding period of just days. Shifts from long to short positions are based on short-term volatility so there is unlikely to be much impact from any underlying positive persistence due to stock selection. None-the-less, we check for survivorship bias by re-running our preliminary trading rule profitability tests over the 2,251 stocks that meet our sufficient trade criteria but are present at the beginning of our sample and not the end. We find the results are virtually identical to those for the stocks that last the entire period so we present these latter results in our paper.

We test the statistical significance of trading rule profits on the individual stocks using both t-tests and a bootstrapping methodology. Both of these techniques are widely used in the literature, however bootstrapping has been shown to have some advantages so we focus on the results generated by this methodology. We also introduce a new approach which is made possible by the large number of stocks we consider. We treat each firm as a Bernoulli trial with the null of zero profits/no predictive power, and a probability of that outcome of 50%. The number of firms with positive profits then has a binomial distribution, which converges to a normal distribution. This allows us to test the statistical significance of the null hypothesis that the trading rules do not generate positive returns on more stocks than would be expected by chance.

Data snooping bias is introduced into research when the same dataset is reused for the purposes of inference or model selection. Sullivan, Timmernman and White (1999) point out that when this re-use occurs there is always the possibility any satisfactory result may simply be due to chance rather than any merit in the technique yielding the results. Data snooping bias need not result from the actions of just one researcher. It is possible many technical trading rules are considered over time and discarded due to lack of profitability. The rules that remain may therefore be profitable simply by chance.

Sullivan, Timmerman and White (1999) propose an appropriate treatment of data-snooping bias that involves adjusting the statistically significance of trading rules to reflect the fact they have come from a larger universe. We purposely study trading rules that have been tested previously on indices to aid comparability with previous studies. It is therefore possible any profitability to these rules is simply due to chance. While we could follow the Sullivan, Timmerman and White (1999) approach and adjust our results for data snooping, our core finding is technical analysis does not have value on the vast majority of individual stocks so we do not proceed with this adjustment as it would only strengthen what is already a very clear result.

Our other results indicate there is some evidence that the moving average and trading range break-out rules are more profitable on small, illiquid stocks but this is not a strong result. There does not appear to be any relationship between a stock's industry and technical analysis profitability. For the small minority of stocks where technical analysis is profitable, the profits are very large (well in excess of reasonable estimates of transaction costs). It is therefore possible technical analysts continue to use these rules for this reason.

The rest of this paper is organized as follows. Section 2 discusses the data and methodology, Section 3 provides the results and discussion, and Section 4 concludes the paper.

Data and Methodology

The data for this study is obtained from the CRSP database and includes all stocks listed on the NYSE and NASDAQ markets over the period 1990 to 2004. For our core results we include only those stocks that are listed at both the beginning and end of the period to keep the methodology manageable. In the first instance all companies that are listed on these two markets at both the beginning and end of the period are included giving a total of 1850 stocks.

A filter, similar to that adopted by Lo et al. (2000), is then applied to ensure that only stocks with sufficient activity to be of interest to technical traders are included. The filter we apply to each company counts the number of non-trades each year and then calculates the percentage of non-trades for that year. Only companies that have a maximum yearly non-trade percentage of less than 5% over all years are included in the final sample. This filter reduced the number of eligible stocks from 1850 to 1065. Of these 1065 stocks, 866 are NYSE stocks and the balance of 199 stocks are NASDAQ stocks. For the stocks finally selected, daily closing prices are collected. As noted in the introduction, we verify that our sample selection does not introduce survivorship bias by running our preliminary analysis on the 2,251 stocks that meet our trade frequency criteria but do not remain listed for the entire 1990-2004 period.

The technical trading rules examined in this study are those that are most commonly studied and documented for use by practitioners (e.g Brock et al, 1992; Hudson et al, 1996). These rules are the variable length moving average rule, (VMA), the fixed length moving average rule, (FMA), and the trading range break-out rule, (TRB). In the case of the VMA, a buy signal is generated when the short-term moving average cuts the long-term moving average from below, or from above for a sell signal. The same applies for the FMA expect in this case the position is held for a fixed number of days. For TRB rules a buy signal is generated when the price moves above a long-term maximum, or below a long-term minimum for a sell signal. For each type of trading rule the short-term was set at one trading day and the long-term at 50, 100, 150, and 200 trading days, in line with other studies that have examined these rules. The final variable that needs to be considered is the amount by which the short-term average breaks through the long-term average or maximum/minimum. For this study we set this level at zero percent.

The main methodology applied in this study is the bootstrapping methodology that originated in Efron (1979). This methodology has a number of advantages of the more standard t-test methodology as it can accommodate the typical characteristics of stock price data such as skewness, leptokurtosis, autocorrelation and conditional heteroskedasticity. In applying the bootstrap methodology a null model has to be chosen to fit the data. There are four standard models used in the literature for the modeling the stock price process. These are a random walk, an autoregressive process of order 1, (AR(1)), a GARCH-M and an E-GARCH. We run our results on all four models and find they are very similar so we present results based on the GARCH-M model, the most commonly used model in the literature.

The GARCH-M model is generally accepted as being the most appropriate for stock price series and is specified below:

$$r_t = \alpha + \gamma\sigma_t^2 + \beta\varepsilon_{t-1} + \varepsilon_t \quad (1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (2)$$

$$\varepsilon_t = \sigma_t z_t \qquad z_t \sim N(0,1) \quad (3)$$

In the GARCH-M model the error term is conditionally normally distributed and serially uncorrelated. The conditional variance, σ_t^2, is a linear function of the square of the last period's conditional variance, which implies positive serial correlation in the conditional second moment of the return process. The conditional returns are a linear function of the conditional variance and the past disturbance, ε_{t-1}. Under this return-generating process, volatility can change over time and the expected returns are a function of the volatility of past returns. For a full description of the GARCH-M process see Engle, Lilien and Robins (1987).

The bootstrap technical constructs a random close-price series where the returns are independently and identically distributed. These series, which are scrambled from the original series, have the same price drift, volatility and unconditional distribution. By comparing the returns of these bootstrap series to the original series, the forecasting power of a particular trading rule can be estimated. For a trading rule to have statistically significant forecasting power at the 5% level more profit should be produced on the random series as compared to the original series less than 5% of the time. As well as adopting the bootstrap methodology, t-tests are also carried out. Again the results between the GARCH-M bootstrap approach and the t-tests are consistent and so the t-test results are not presented here.

We also introduce a new approach which is made possible by the large number of stocks we consider. We treat each firm as a Bernoulli trial with the null of zero profits/no predictive power, and a probability of that outcome of 50%. The number of firms with positive profits has a binomial distribution, which converges to the normal distribution. This allows us to test the statistical significance of the null hypothesis that the trading rules are do not generate positive returns on more stocks than would be expected by chance.[1]

One final point that should be noted relates to the investing options open to the technical trader. The CRSP data gives only closing prices for the stocks considered in this study. In reality it is not particularly realistic for a trader to be able to invest in a stock at the closing price on the day a buy or sell signal is generated with that closing price. The investment would most likely take place at the following day's opening price but this data was not available. Results are run assuming investment at the closing prices on both the signal day and the following day. The results presented here are for investment on the day following the signal and as results are consistent by both approaches it is reasonable to conclude that using the following day's opening price would also have little impact on these results.

[1] We wish to thank an anonymous referee at the 2006 Annual FMA meeting for this suggestion.

Results

The bootstrap results for the GARCH-M model with 1-day lag for order execution for the entire period and two sub-periods from 1990 to 1997 and from 1998 to 2004 for both the NSYE and NASDAQ stocks are presented in Table 1. In the case of the NYSE stocks these two periods roughly coincide with bull and bear markets. As can be seen, the number of statistically significant positive return companies is small for all trading rules over all periods for both markets. There is no noticeable difference between the three trading rules examined or between the holding periods used, other than that generally more NASDAQ stocks show significantly positive returns in the later period as compared to the earlier period. On average the trading rules give significantly positive results on only 3% of NYSE stocks and 2.8% of NASDAQ stocks.

INSERT TABLE 1 HERE

We further consider the significance of the results from the viewpoint that if the trading rule has no predictive power, the rule should generate positive profits 50% of the time. Our test considers whether there is statistically significantly more or less instances of a rule producing positive profits than would be expected by chance. The test draws from the binomial distribution which can be approximated by the normal distribution given our large sample size. We present the results for the VMA trading rules in Table 2. These are consistent with the results for the other trading rules. In all cases the z-statistic is negative and statistically significant at the 1% or 5% level. This suggests that each VMA rule generates fewer instances of positive profit than would be expected by chance, and provides confirmation of the results displayed in Table 1.

INSERT TABLE 2 HERE

We consider differences between the size and liquidity of stocks that the technical trading rules produce positive and statistically significant profits on (at the 5% level) versus those that they do not in two different ways. Firstly, we generate t-statistics by comparing the size and liquidity of the stocks which generate positive statistically significant returns to those which do not. These results indicate that size and volume do influence the likelihood of stocks generating positive statistically significant returns, particularly in the case of the NASDAQ stocks. For the NYSE stocks, three trading rules give significant t-statistics for size, and two for volume. For the NASDAQ stocks, six trading rules give significant t-statistics for size and eight for volume. In all cases the t-statistics give a negative value indicating the smaller size and smaller volume stocks are more likely to generate positive statistically significant returns than larger size and larger volume stocks.

Under the second technique, whose results are presented in the columns three and four, we rank all stocks from smallest to largest based on both average size (Table 3) and average volume turnover (Table 4). The stocks are then placed in quintiles with the lowest 20% being allocated a value of 1, the next 20% a value of 2 and so on up to the highest 20% being allocated a value of 5. We then partition stocks into two groups, those for which statistically significant profits (at the 5% level) are generated and those for which there is no statistically significant profit.

An average score of 3 for the statistically significantly positive subset of stocks for a trading rule indicates that average size or average volume turnover for those stocks is the same as the average for all stocks in our sample. An average score of less (more) than 3 indicates the stocks for which positive profits are earned are smaller (larger) and less (more) liquid than the stocks in our sample for which the trading rule does not produce statistically significant profits.

In contrast to the t-statistic results, these results indicate that there is very little difference between the size and liquidity of stocks that produce statistically significant positive profits and those that do not. The average size of the statistically significant positive profit stocks across all trading rules is 3.07 for NYSE stocks and 3.00 for NASDAQ stocks. This compares to an average size of 3.00 and 2.99 for non-statistically significant positive profit stocks for the NYSE and NASDAQ respectively. Similarly, the liquidity results in Table 4 indicate that the statistically significant positive profit stocks are more liquid but the difference is small. For instance, the average liquidity level of the statistically significant positive profit NYSE stocks across all trading rules is 3.19, compared to 2.99 for non- statistically significant positive profit NYSE stocks.

INSERT TABLES 3 AND 4 HERE

Table 5 gives the results for the VMA (1-50) and VMA (1-200) trading rules on NYSE stocks by industry. The industry results are similar across all trading rules so we present these rules only. The number of statistically significant stocks for the NASDAQ was too low for this analysis to be meaningful as the industry classifications are too concentrated. The industry classifications used here follow those of Moskowitz and Grinblatt, (1999). As can be seen from Table 5, there is no indication of any industry bias in the results with the numbers of significantly positive stocks being randomly spread across the different industries. The highest number of significantly positive stocks is shown to occur under the Financial classification but this classification also has the largest number of entrants and the result.

INSERT TABLE 5 HERE

The results in Table 6 look at the economic significance of all VMA trading rules where statistically significant positive returns are made for both NYSE and NASDAQ stocks. The level of economic significance is determined by the size of the break-even transaction costs, in accordance with the approach developed by Bessembinder and Chan (1998). The economic significance is substantial for the 100, 150, and 200 day trading rules, with break even transaction costs ranging from 2.12% to 7.79% for NYSE stocks and 5.65% to 6.68% for NASDAQ stocks. These profits, which are similar to the equivalent profits for the FMA and TRB rules we test, increase as the number of trades decline.

The profits are substantially higher than reasonable estimates of transaction costs, which include bid-ask spreads and commissions. Jones (2002) reports that the average one-way commissions on round-lot transactions in NYSE stocks were around 0.3% prior to the 1930s; they then steadily rose to a peak of approximately 0.9% in the mid-1970s, prior to the Securities and Exchange Commission's (SEC) breaking of the commission cartel. Commissions then began dramatically falling and are down to approximately 0.1% today. Commissions vary based on who is doing the trading. Floor traders face lower commissions than do money managers, who-in turn- face lower commissions than do private individuals. Jones (2002) reports that average bid-ask spreads declined from 1.4% in the 1930s to 0.2% in 2000.

It therefore appears that when the technical trading rules do generate profits the profits after transaction costs are substantial. This may be part of the explanation as to why technical analysis continues to be so popular with practitioners despite the evidence that it is not generally profitable. It is possible the behavioral biases that are inherent in the investors' decision making process results in investors discounting the impact of consistent losses due to the large profits that occasionally occur.

INSERT TABLE 6 HERE

Conclusion

This paper investigates whether the popularity of technical trading rules with practitioners is due to their profitability on a small subset of stocks with certain size, liquidity, and industry characteristics. It is possible that some stocks that are not included in market indices, the focus of previous technical analysis studies, have characteristics that can be profitability captured by technical trading rules. We consider this using popular moving average and trading break-out rules on individual U.S. stocks over the 1990-2004 period.

We find that these rules are not profitable when applied to the vast majority of stocks. This result is robust to different time periods and different markets (NYSE and NASDAQ). There is some evidence that these trading rules are more profitable on small, illiquid stocks, but this result is not strong. We do not find any link between a firm's industry and the profitability of technical analysis.

When a trading rule does produces statistically significant profits on a stock, these profits tend to be greater for longer decision period rules. Also the profits tend to be considerably larger than reasonable estimates of transaction costs. This may explain why practitioners continue to use technical analysis despite it not generating profits on a consistent basis.

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TABLE 1
Bootstrap Results

Bootstrap results for the VMA, FMA, and TRB technical trading strategies. (1, 50), (1, 100), (1, 150), and (1, 200) rules are tested in each instance. The results relate to entering positions on the day after a signal and cover both NYSE and NASDAQ stocks for the whole period, 1990 to 2004 and for two sub-periods, 1990 to 1997 and 1998 to 2004. The number of stocks with significantly positive returns is shown as at the 5% confidence level.

	NYSE			NASDAQ		
Rule	**No. Sig Profitable**	**No. Not Sig Profitable**	**Total**	**No. Sig Profitable**	**No. Not Sig Profitable**	**Total**
Panel A: Entire Sample (1990 - 2004)						
VMA (1,50)	33	833	866	6	193	199
VMA (1,100)	25	841	866	2	197	199
VMA (1,150)	14	852	866	3	196	199
VMA (1,200)	12	854	866	2	197	199
FMA (1,50)	26	840	866	5	194	199
FMA (1,100)	26	840	866	5	194	199
FMA (1,150)	27	839	866	10	189	199
FMA (1,200)	23	843	866	5	194	199
TRB (1,50)	27	839	866	7	192	199
TRB (1,100)	22	844	866	10	189	199
TRB (1,150)	31	835	866	8	191	199
TRB (1,200)	29	837	866	10	189	199
Panel B: Sub Period 1 (1990 - 1997)						
VMA (1,50)	27	839	866	6	193	199
VMA (1,100)	22	844	866	2	197	199
VMA (1,150)	12	854	866	1	198	199
VMA (1,200)	5	861	866	3	196	199
FMA (1,50)	19	847	866	3	196	199
FMA (1,100)	26	840	866	9	190	199
FMA (1,150)	32	834	866	9	190	199
FMA (1,200)	33	833	866	7	192	199
TRB (1,50)	31	835	866	4	195	199
TRB (1,100)	24	842	866	4	195	199
TRB (1,150)	35	831	866	4	195	199
TRB (1,200)	39	827	866	2	197	199
Panel C: Sub Period 2 (1998 - 2004)						
VMA (1,50)	25	841	866	6	193	199
VMA (1,100)	16	850	866	4	195	199
VMA (1,150)	18	848	866	5	194	199
VMA (1,200)	14	852	866	3	196	199
FMA (1,50)	45	821	866	7	192	199
FMA (1,100)	37	829	866	11	188	199
FMA (1,150)	39	827	866	10	189	199
FMA (1,200)	27	839	866	6	193	199
TRB (1,50)	38	828	866	7	192	199
TRB (1,100)	38	828	866	7	192	199
TRB (1,150)	25	841	866	6	193	199
TRB (1,200)	30	836	866	5	194	199

TABLE 2
Bernouli Results

Bernouli statistical significance results based on 1-day lag for VMA for (1, 50), (1, 100), (1, 150), and (1, 200) rules on NYSE and NASDAQ stocks for the whole period, 1990 to 2004. The number of positive stocks is the total number of stocks giving positive returns irrespective of the significance of those returns. * statistically significant at the 5% level, ** statistically significant at the 1% level.

	N	P	Mean	No. Pos	Sigma	z-stat
Panel A: NYSE Positive						
VMA 1-50	866	0.5	433	387	14.71	-3.126**
VMA 1-100	866	0.5	433	349	14.71	-5.709**
VMA 1-150	866	0.5	433	351	14.71	-5.573**
VMA 1-200	866	0.5	433	263	14.71	-11.554**
Panel B: NASDAQ Positive						
VMA 1-50	199	0.5	99.5	84	7.05	-2.198*
VMA 1-100	199	0.5	99.5	75	7.05	-3.474**
VMA 1-150	199	0.5	99.5	71	7.05	-4.041**
VMA 1-200	199	0.5	99.5	71	7.05	-4.041**

TABLE 3
Differences in Statistical Significance by Size

Size differences based on 1-day lag bootstrap results for all trading rules the period 1990 to 2004. The size t-stat column is the t-statistic from comparing the size of stocks which generate positive statistically significant profits to those which do not generate statistically significant positive profits. The other two columns contain results generate from ranking all stocks from smallest to largest on average size. Stocks are then allocated a number from 1 to 5 based on their average size with the smallest 20% of stocks allocated the number 1 and so on. The stocks that have statistically significant positive profitability and no significant profitability are then identified and the average of these numbers for both groups of stocks is calculated. An average value of 3 indicates that there is no difference between profitable stocks and non-profitable stocks based on size. * statistically significant at the 5% level, ** statistically significant at the 1% level.

		Average Size	
Rule	**Size T-Stat**	**No. Sig Profitable**	**No. Not Sig Profitable**
Panel A: NYSE			
VMA (1,50)	-2.082*	3.18	3.00
VMA (1,100)	0.777	3.16	3.00
VMA (1,150)	-1.138	3.21	3.00
VMA (1,200)	0.787	3.33	3.00
FMA (1,50)	-2.023*	2.65	3.01
FMA (1,100)	0.591	2.73	3.01
FMA (1,150)	-1.857	2.89	3.01
FMA (1,200)	-2.021*	3.09	3.00
TRB (1,50)	-0.853	3.30	2.99
TRB (1,100)	-1.108	3.00	3.00
TRB (1,150)	0.279	3.10	3.00
TRB (1,200)	1.067	3.24	2.99
Average		3.07	3.00
Panel B: NASDAQ			
VMA (1,50)	0.876	3.33	2.98
VMA (1,100)	-2.465*	2.50	2.99
VMA (1,150)	0.931	3.33	2.98
VMA (1,200)	-2.088*	3.00	2.99
FMA (1,50)	0.033	4.00	2.96
FMA (1,100)	-0.655	3.60	2.97
FMA (1,150)	-1.869	2.70	3.01
FMA (1,200)	-2.593**	3.00	2.99
TRB (1,50)	-2.621**	2.43	3.01
TRB (1,100)	-2.440*	2.60	3.01
TRB (1,150)	-2.675**	2.25	3.02
TRB (1,200)	-1.009	3.20	2.98
Average		3.00	2.99

TABLE 4
Differences in Statistical Significance by Liquidity

Volume differences based on 1-day lag bootstrap results for all trading rules the period 1990 to 2004. The Volume t-stat column is the t-statistic from comparing the volume of stocks which generate positive statistically significant profits to those which do not generate statistically significant positive profits. The other two columns contain results generate from ranking all stocks from smallest to largest on average volume. Stocks are then allocated a number from 1 to 5 based on their average volume with the smallest 20% of stocks allocated the number 1 and so on. The stocks that have statistically significant positive profitability and no significant profitability are then identified and the average of these numbers for both groups of stocks is calculated. An average value of 3 indicates that there is no difference between profitable stocks and non-profitable stocks based on volume. * statistically significant at the 5% level, ** statistically significant at the 1% level.

		Average Volume	
Rule	**Vol T-Stat**	**No. Sig Profitable**	**No. Not Sig Profitable**
Panel A: NYSE			
VMA (1,50)	-1.185	3.30	2.99
VMA (1,100)	0.606	3.28	2.99
VMA (1,150)	-1.470	3.21	2.99
VMA (1,200)	0.794	3.50	2.99
FMA (1,50)	-2.005*	2.69	3.01
FMA (1,100)	-0.397	2.73	3.01
FMA (1,150)	-1.688*	3.07	3.00
FMA (1,200)	0.174	3.17	2.99
TRB (1,50)	0.226	3.52	2.98
TRB (1,100)	0.126	3.05	3.00
TRB (1,150)	0.282	3.29	2.99
TRB (1,200)	1.112	3.48	2.98
Average		3.19	2.99
Panel B: NASDAQ			
VMA (1,50)	0.828	3.33	2.98
VMA (1,100)	-3.114**	2.50	2.99
VMA (1,150)	0.912	3.33	2.98
VMA (1,200)	-3.286**	3.00	2.99
FMA (1,50)	-0.456	4.00	2.96
FMA (1,100)	-0.549	3.40	2.98
FMA (1,150)	-2.137*	3.00	2.99
FMA (1,200)	-3.169**	3.00	2.99
TRB (1,50)	-3.286**	2.57	2.57
TRB (1,100)	-2.675**	2.80	3.00
TRB (1,150)	-3.254**	2.63	3.01
TRB (1,200)	-2.154*	2.80	3.00
Average		3.03	2.95

TABLE 5
Differences in Statistical Significance by Industry

All NYSE stocks are classified by their industry and the number of statistically significant positive (at the 5% level) and not statistically significant return stocks is counted for each industry. The industry classifications are those given in Moskowitz and Grinblatt, (1999). These results are for the VMA (1, 50) and VMA (1, 200) rules and are based on 1-day lag bootstrap results for the entire period 1990 to 2004. Total 1 is the total number of companies that remained in the same industry for 70% or more of the time. These are allocated across the 20 categories. Total 2 is the total number of companies in our sample.

	VMA 1-50 Rule			VMA 1-200 Rule		
Industry Name	**No. Sig Profitable**	**No. Not Sig Profitable**	**Total**	**No. Sig Profitable**	**No. Not Sig Profitable**	**Total**
Mining	2	41	43	1	42	43
Food	3	23	26	1	25	26
Apparel	0	9	9	0	9	9
Paper	0	13	13	0	13	13
Chemical	0	40	40	1	39	40
Petroleum	1	8	9	0	9	9
Construction	0	4	4	0	4	4
Prim. Metals	0	16	16	0	16	16
Fab. Metals	0	11	11	0	11	11
Machinery	5	33	38	1	37	38
Electrical Equip	0	26	26	0	26	26
Transport Equip	0	18	18	0	18	18
Manufacturing	0	18	18	0	18	18
Railroads	0	3	3	0	3	3
Other Transport	0	12	12	0	12	12
Utilities	2	75	77	1	76	77
Dept. Stores	0	8	8	0	8	8
Retail	3	45	48	0	48	48
Financial	11	211	222	5	217	222
Other	1	94	95	2	93	95
Total 1	28	708	736	12	724	736
Total 2	33	833	866	12	854	866

TABLE 6
Economic Significance

The economic significance of the VMA trading rules is presented to show the returns to the statistically significant positive stocks. The methodology used to calculate economic significance is based on Bessembinder and Chan, (1998). All results are based on 1-day lag for the entire period, 1990 to 2004.

Rule	Number of Stocks	Buy	Sell	Buy-Sell	Buy-and-Hold	Excess Trading Rule	Trades Per Year	Break Even Transaction Costs
Panel A: NYSE								
VMA 1-50	33	11.59%	-7.81%	19.40%	3.44%	15.96%	16.07	0.99%
VMA 1-100	25	14.87%	-9.99%	24.86%	3.98%	20.88%	9.84	2.12%
VMA 1-150	14	12.83%	-10.82%	23.65%	1.28%	22.37%	6.2	3.61%
VMA 1-200	12	16.56%	-20.22%	36.78%	-0.99%	37.76%	4.84	7.79%
Panel B: NASDAQ								
VMA 1-50	6	19.18%	-6.03%	25.21%	12.56%	12.65%	17.48	0.72%
VMA 1-100	2	27.85%	-21.09%	48.93%	7.10%	41.83%	7.4	5.65%
VMA 1-150	3	24.70%	-17.26%	41.96%	7.10%	34.86%	6.34	5.50%
VMA 1-200	2	11.83%	-17.40%	29.23%	-5.64%	34.87%	5.22	6.68%