Re-Examining the Profitability of Technical Analysis with White's Reality Check

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Abstract

In this paper, we re-examine the profitability of technical analysis using the Reality Check of White (2000, *Econometrica*) that corrects the data snooping bias. Comparing to previous studies, we study a more complete "universe" of trading techniques, including not only simple trading rules but also investor's strategies, and we test the profitability of these rules and strategies with four main indices from both relatively mature and young markets. It is found that profitable simple rules and investor's strategies do exist with statistical significance for NASDAQ Composite and Russell 2000 but not for DJIA and S&P 500. Moreover, the best rules for NASDAQ Composite and Russell 2000 outperform the buy-and-hold strategy in most in- and out-of-sample periods, even when transaction costs are taken into account. We also find that investor's strategies are able to improve on the profits of simple rules and may even generate significant profits from unprofitable simple rules.

Keywords: data snooping, investor's strategies, stationary bootstrap, technical analysis, trading rules, White's Reality Check.

1 Introduction

Technical analysis has been widely applied by practitioners to analyze financial data and make trading decisions for decades. This method relies on mechanical trading rules and strategies to generate buy and sell signals. Thus, whether these trading techniques indeed result in significant profit has been a long-debated issue since Fama and Blume (1966). Recent empirical studies, however, find more and more supporting evidences for the profitability of techncial analysis, including, among others, Sweeney (1986, 1988), Brock, Lakonishok, and LeBaron (1992), Blume, Easley, and O'Hara (1994), Chan, Jegadeesh, and Lakonishok (1996, 1999), Gencay (1996, 1998, 1999), Neely, Weller, and Dittmar (1997), Brown, Goetzmann, and Kumar (1998), Rouwenhorst (1998), Allen and Karjalainen (1999), Chang and Osler (1999), Neely and Weller (1999), Chan, Hameed, and Tong (2000), and Lo, Mamaysky, and Wang (2000). These results suggest that technical analysis is popular because it can "beat the market."

On the other hand, Lo and MacKinlay (1990) and Brock, Lakonishok, and LeBaron (1992) raised a concern about the data snooping bias that may arise in many empirical studies. Such bias is mainly a consequence of data reuse. In the context of evaluating technical analysis, it is conceivable that, by repeatedly examining different trading rules using the same data set, some rules would appear to be profitable, yet such profitability may simply be due to luck. This concern is shared by academic and market professionals; see, e.g., Allen and Karjalainen (1999), LeBaron and Vaitilingam (1999), and Ready (2002). To avoid spurious inferences resulted from data snooping, White (2000) proposed a formal test, now also known as White's Reality Check, on whether there exists a superior model (rule) in a "universe" of models (rules). Sullivan, Timmermann, and White (1999), henceforth STW, and White (2000) applied this test and found that there exists *no* profitable simple trading rule for Dow Jones Industrial Average (DJIA) index, S&P 500 index, and S&P 500 futures. This method has also been applied by Sullivan, Timmermann, and White (2001) to demonstrate that the well known calendar effect is in fact a statistically insignificant phenomenon.

It may be too early to declare the obituary for technical analysis, however. To properly quantify the effect of data snooping, White's Reality Check requires constructing a "universe" of the trading rules considered by previous researchers and practitioners. To this end, STW collected a total of $7,846$ trading rules, drawn from 5 commonly used classes of rules in financial markets. Although $7,846$ is a large number, this collection of rules may not be sufficient for testing the profitability of technical analysis using Reality Check. First, several well known classes of trading rules, such as momentum strategies and head-and-shoulders, were not included. Second, STW considered only simple trading rules but not investor's strategies. In practice, an investor need not stick to only one simple rule but may employ a complex trading strategy that utilizes the information from many rules. Taking these rules and strategies into account should be able to enlarge the "effective span" of the trading rules studied in STW and hence may affect the result of Reality Check. Moreover, STW analyzed only the samples of more "mature" markets, such as DJIA and S&P 500. Since the last decade, small-cap and technology stocks have played more active roles in contemporary markets. It is therefore also interesting to find out whether STW's claim remains valid in the samples of other relatively "young" markets.

In this paper, we extend the analysis of STW and White (2000) along the following lines. First, White's Reality Check is applied to an expanded "universe" of $39,832$ simple trading rules, "contrarian" rules, and investor's strategies. Second, our study covers the indices of both "mature" and "young" markets: DJIA, S&P 500, NASDAQ Composite, and Russell 2000. Third, we consider transaction costs in evaluating the performance of trading rules. It is found that, similar to Siegel (2002, pp. 290–297), profitable trading rules and investor's strategies do exist with statistical significance for NASDAQ Composite and Russell 2000. On the other hand, the claims of STW and White (2000) still stand for DJIA and S&P 500. We also find that investor's strategies are able to improve on the profits of simple rules. It is even more interesting to observe that some investor's strategies constructed from unprofitable simple rules can generate significant profits. These results show that investor's learning and decision processes are important for technical analysis. Therefore, the profitability of technical analysis can not be properly evaluated without considering investor's strategies. Further examination shows that the best rules for NASDAQ Composite and Russell 2000 outperform the buy-and-hold strategy in most in- and out-of-sample periods, even when transaction costs are taken into account. Our results are thus in line with the claim that the degree of market efficiency is related to market maturity.

This paper is organized as follows. White's Reality Check is briefly discussed in

Section 2. The trading rules and investor's strategies included in our expanded "universe" are described in Section 3. Section 4 presents the empirical results. Section 5 concludes the paper. The parameter values of the trading rules and strategies are given in Appendix.

2 White's Reality Check

Data snooping is quite common in empirical economic studies. As economic activities in the real world are not experimental in general, researchers often have little choice but rely on the same data set. In testing a model on a given data set, the data snooping bias may arise when previous test results based on the same data set are ignored. Lo and MacKinlay (1990) showed that even slight prior information has a dramatic impact on the resulting statistical inferences.

In the literature, there are basically two different approaches to tackling the data snooping bias. The first approach focuses on data and tries to avoid re-using the same data set. This may be done by testing a model with a different but comparable data set; see e.g., Lakonishok, Shleifer, and Vishny (1994) and Chan, Karceski, and Lakonishok (1998). When such data are not available, one may adopt a large data set and validate the test using several subsamples; see e.g., Brock, Lakonishok, and LeBaron (1992), Rouwenhorst (1998, 1999), Gencay (1998), and Fernandez-Rodriguez et al. (2000). Such sample splitting is, however, somewhat arbitrary and hence may lack desired objectivity. A more formal approach is to consider all possible models and construct a test with properly controlled test size (type I error). For example, Lakonishok and Smidt (1988) suggested using the Bonferroni inequality to bound the size of each individual test. Unfortunately, this method is not appropriate when the number of hypotheses (models) being tested is large, as in the case of testing the profitability of technical analysis. The Reality Check proposed by White (2000) follows the latter approach but does not suffer from this problem.

Given a performance criterion, let φ_k $(k = 1, \dots, M)$ denote the performance measure of the k-th model (rule) relative to the benchmark model (rule). The null hypothesis is that there does not exist a superior model (rule) in the collection of M models (rules) under the given performance criterion. That is,

$$H_0\colon \max_{k=1,\dots,M} \varphi_k \leq 0. \tag{1}$$

Rejecting (1) implies that there exists at least one model (rule) that outperforms the benchmark. Testing this hypothesis is cumbersome when all models (rules) are evaluated using the same data set and also when M is large.

In the current context, φ_k may be the mean return $\mathbb{E}(f_k)$, where f_k is the return of the k-th trading rule relative to the benchmark rule. Let y_t denote the rate of return of an asset at time t and $s_{k,t-1}$ the signal function of the k-th rule based on the information up to time $t-1$. Here, $s_{k,t-1}$ takes the value 1 for a long position, 0 for no position, or -1 for a short position. Setting the rule of no position (zero return) at all time as the benchmark, the t-th observation of f_k is $f_{k,t} = \ln(1+y_t s_{k,t-1})$, $t = 1, \ldots, n$.[1] Thus, when $\varphi_k = \mathbb{E}(f_k)$, it is natural to base a test of (1) on the maximum of the normalized sample average of $f_{k,t}$:

$$\overline{V}_n = \max_{k=1,\ldots,M} \sqrt{n}\, \bar{f}_k, \tag{2}$$

where $\bar{f}_k = \sum_{t=1}^n f_{k,t}/n$. When φ_k is the Sharpe ratio of the k-th rule relative to the risk-free interest rate r:

$$\varphi_k = \frac{\mathbb{E}(\eta_k) - \mathbb{E}(r)}{\{\mathbb{E}(\eta_k^2) - [\mathbb{E}(\eta_k)]^2\}^{1/2}},$$

where η_k is such that its t-th observation is $\eta_{k,t} = y_t s_{k,t-1}$, we can compute its sample counterpart as

$$\bar{f}_k = \frac{\frac{1}{n}\sum_{t=1}^n (\eta_{k,t} - r_t)}{\left[\frac{1}{n}\sum_{t=1}^n \eta_{k,t}^2 - \left(\frac{1}{n}\sum_{t=1}^n \eta_{k,t}\right)^2\right]^{1/2}}.$$

Basing on this $\bar{f}_k$, the statistic (2) can still be used to test (1).

White (2000) suggested using the stationary bootstrap method of Politis and Romano (1994) to compute the p-values of $\overline{V}_n$. Let $f_k^*(j)$ denote the j-th bootstrapped sample of f_k and $\bar{f}_k^*(j) = \sum_{t=1}^n f_{k,t}^*(j)/n$ its sample average. We then obtain the empirical distribution of $\overline{V}_n^*$ with the realizations:

$$\overline{V}_n^*(j) = \max_{k=1,\ldots,M} \sqrt{n}(\bar{f}_k^*(j) - \bar{f}_k), \qquad j = 1, \ldots, B. \tag{3}$$

Corollary 2.4 of White (2000) showed that, under suitable regularity conditions, the distributions of $\overline{V}_n^*$ and $\overline{V}_n$ are asymptotically equivalent. The Reality Check p-value is

[1]Note that s_k depends on unknown parameters and must be evaluated using some parameter estimates. For notational convenience, we suppress the arguments of s_k and still denote the estimated return as f_k.

then obtained by comparing $\overline{V}_n$ with the quantiles of the empirical distribution of $\overline{V}_n^*$. The null hypothesis is rejected whenever the p-value is less than a given significance level.

3 An Expanded Universe of Trading Rules and Strategies

A crucial step in White's Reality Check is to construct a "universe" of trading rules and strategies for evaluation. There are some limitations of STW's universe, however. First, it contains only 5 classes of simple trading rules. Second, it ignores investor's strategies that embody investor's decision process based on the information from many simple rules. Although most studies of technical analysis focus only on simple rules, investor's strategies should be practically more relevant. In this paper we expand the universe of STW to a collection of $39,832$ rules and strategies, including 12 classes of $18,326$ simple rules, $18,326$ corresponding "contrarian" rules, and $3,180$ investor's strategies. Note that not only investor's strategies but also contrarian rules have not been considered in the literature. This collection greatly enlarges the "effective span" of the rules in STW. All the rules and strategies considered in this study are summarized in Table 1 and will be discussed subsequently.

3.1 Simple Trading Rules

There are 12 classes of simple trading rules in our expanded universe; 5 of them: filter rules (FR), moving averages (MA), support-and-resistance (SR), channel break-outs (CB), and on-balance volume averages (OBV) were those originally used to form the universe in STW. We follow STW to construct $7,846$ trading rules for these 5 classes; see STW for details. The other classes of simple rules are also well known among market professionals, including momentum strategies in price (MSP), momentum strategies in volume (MSV), head-and-shoulders (HS), triangle (TA), rectangle (RA), and double tops and bottoms (DTB), and broadening tops and bottoms (BTB). Momentum strategies have been widely analyzed in the literature; see e.g., LeBaron (1991), Chan, Jegadeesh, and Lakonishok, (1996, 1999), Rouwenhorst (1998, 1999), and Chan, Hameed, and Tong (2000). All other rules were also studied by Lo, Mamaysky, and Wang (2000); Chang and Osler (1999) focused on the HS rules.

Table 1: The expanded universe of trading rules and strategies.

Simple trading rules	18,326
Filter Rules (FR)	497
Moving Averages (MA)	2,049
Support and Resistance (SR)	1,220
Channel Break-Outs (CB)	2,040
On Balance Volume Averages (OBV)	2,040
Momentum Strategies in Price (MSP)	1,760
Momentum Strategies in Volume (MSV)	1,760
Head and Shoulders (HS)	1,200
Triangle (TA)	720
Rectangle (RA)	2,160
Double Tops and Bottoms (DTB)	2,160
Broadening Tops and Bottoms (BTB)	720
Contrarian trading rules	18,326
Investor's strategies	3,180
Learning Strategies (LS)	1,404
Vote Strategies (VS)	888
Position Changeable Strategies (PCS)	888
Total	39,832

A momentum strategy adopted by market practitioners is determined by an "oscillator" constructed from a momentum measure. The momentum measure used in this study is the rate of change (ROC). Specifically, the m-day ROC at time t is $(q_t - q_{t-m})/q_{t-m}$, where q_t is the closing price or closing volume at time t. Pring (1991, 1993) recommended three oscillators: simple oscillator, moving average oscillator, and cross-over moving average oscillator. The simple oscillator is just the m-day ROC; the moving average oscillator is the w-day moving average of m-day ROC with $w \leq m$; the cross-over moving average oscillator is the ratio of the w_1-day moving average to the w_2-day moving average (both based on m-day ROC) with $w_1 < w_2$. An overbought/oversold level k (say 5% or 10%) is needed to determine whether a position should be initiated. When the oscillator crosses the overbought level from below, it is a signal for initiating a long position. On the other hand, a signal for short position will be issued when the oscillator crosses the oversold level from above. We set that, once a position is initiated, the investor will hold the position for fixed holding days f and then liquidate it. There are 1,760 rules in the MSP class and 1,760 rules in the MSV class; the values of the parameters m, w, k and f are given in Appendix A.1.

The rules in the HS class are also well known in financial markets. The HS rules are determined by the top-and-bottom patterns of price movements. For a given sample period with five equal subperiods, each with n days, a HS pattern is such that the price sequentially exhibits left shoulder (top), left trough (bottom), head (top), right trough (bottom), and right shoulder (top) in these subperiods. We require the two shoulders (troughs) being approximately equal such that their differences are no more than a differential rate x. To identify this pattern more easily, it is also required that the maximal price of the head subperiod must be the highest price in all superiods. Moreover, the minimal prcies in the head and shoulder subperiods must be higher than those of adjacent trough subperiods, and the maximal prices of two trough subperiods must be lower than those of the head and shoulder subperiods. Once an HS pattern is completed, future price movement is expected to decline because it is believed that the falling trend would prevail after such a struggle of price adjustment. Thus, an HS pattern serves as a signal of taking a short position. For these trading rules, we considered three liquidation methods: fixed holding days f, stoploss rate r, and fixed liquidation price (depending on the parameter d). There are 1,200 rules in the HS class; the values of the parameters in this class are discussed in Appendix A.2.

The trading rules of the TA class are also based on price movements that exhibit a series of top-and-bottom patterns. To identify a triangle, we again divide a given period into five equal subperiods, each with n days, orderly numbered from 1 to 5. Let M_i and m_i denote, respectively, the maximum and minimum in subperiod i. A triangle is formed when either one of the two patterns below holds: (1) M_1, M_3, M_5 are tops such that $M_1 > M_3 > M_5$, and m_2, m_4 are bottoms such that $m_2 < m_4$; (2) m_1, m_3, m_5 are bottoms such that $m_1 < m_3 < m_5$, and M_2, M_4 are tops such that $M_2 > M_4$. Moreover, the minimal closing price of a top subperiod is required to be higher than that of adjacent bottom subperiod(s), and the maximal closing price of a top subperiod is required to be higher than that of adjacent bottom subperiod(s). The trading rules of the RA class are determined in a similar fashion. A rectangle is formed when the tops M_1, M_3, M_5 (or M_2, M_4) lie near an upper horizontal line and the bottoms m_2, m_4 (or m_1, m_3, m_5) lie near a lower horizontal line. By "near a horizontal line" we mean the difference between the tops (bottoms) are within certain bounds (e.g., ± 0.005, ± 0.0075). Once a triangle (rectangle) is completed, it will be a signal for taking a long (short) position if the future closing price exceeds the latest top (or falls below the latest bottom) by a fixed proportion x, known as the "trend filter." We also considered three liquidation methods for the TA and RA classes: fixed holding days f, stoploss rate r, and day filter d. There are 720 rules in the TA class and 2,160 rules in the RA class; the parameter values of these two classes are discussed in Appendix A.3 and A.4, respectively.

The DTB class includes two patterns: double-top and double-bottom. Dividing a given sample period into three equal subperiods, each with n days, a double-top is formed by two equal tops (maxima) in the first and last subperiods and a bottom (minimum) in the second subperiod. Similarly, a double-bottom is formed by two equal bottoms (minima) in the first and last subperiods and a top (maximum) in the second subperiod. The tops (bottoms) are considered equal if they are within certain bounds of their average (e.g., $\pm 0.005, \pm 0.0075$). To identify the double-top (double-bottom) pattern more easily, we require the minimal (maximal) closing price of the second subperiod is at least g percent lower (higher) than the average of two tops (bottoms). Similar to the TA and RA classes, the minimal closing price of a top subperiod is required to be higher than that of adjacent bottom subperiod, and the maximal closing price of a top subperiod is required to be higher than than that of adjacent bottom subperiod. Also, a trend filter is also needed to determine future price movement. If the closing price in a following day exceeds the latest top (falls below the latest bottom) by a trend filter x, it is a sign of long (short) position. We again consider three liquidation methods: fixed holding days f, stoploss rate r, and day filter d. There are 2,160 rules in the DTB class; the parameter values of this class are provided in Appendix A.5.

The trading rules in the BTB class, similar to those in the TA class, are determined by the top-and-bottom patterns in five subperiods. The difference is that TA requires "convergence" in shape, whereas BTB corresponds to "divergence" in shape. More specifically, again let M_i and m_i denote, respectively, the maximum and minimum in subperiod i. A BTB pattern is formed if one the two conditions below holds: (1) M_1, M_3, M_5 are tops such that $M_1 < M_3 < M_5$, and m_2, m_4 are bottoms satisfying $m_2 > m_4$; (2) m_1, m_3, m_5 are bottoms such that $m_1 > m_3 > m_5$, and M_2, M_4 are tops satisfying $M_2 < M_4$. The parameters of this class are set as those in the TA class (see A.3), and there are 720 rules in the BTB class.

3.2 Contrarian Trading Rules

"Contrarian" rules are common in trader's handbooks (e.g., LeBaron and Vaitilingam, 1999, and Siegel, 2002), but they were rarely inspected in previous empirical studies. Corresponding to each simple trading rule, a contrarian rule is such that a long signal of the simple rule suggests a short position and vice versa. Typically, technical analysts believe that the trading signals of some trading rules are caused by price deviations far from the current state and hence signify changes in trend. The rationale of contrarian rules is that such price deviations might still be temporary so that the market will return to its original state sooner or later. In our study, there are $18,326$ simple trading rules and hence $18,326$ corresponding contrarian rules.

3.3 Investor's Strategies

For technical analysts, investor's strategies are usually more important than simple trading rules. Although simple rules may be informative in some cases, it is hard to believe that technical investors stick to only a single rule without incorporating other available information. Pring (1991) pointed out: "No single indicator can ever be expected to signal all trend reversals, and so it is essential to use a number of them together to build up a consensus" (p. 9). Indeed, investor's strategies are practically useful because they rely on the information generated from many simple rules and make trading decisions through a complex evaluation process. Despite their practical relevance, investor's strategies have not been examined in previous studies of technical analysis. In this paper, we consider three classes of investor's strategies: learning strategies (LS), vote strategies (VS), position changeable strategies (PCS), leading to a total of $3,180$ strategies.

The strategies of the LS class allow investors to switch their positions by following the best-performed rule within a rule class. In this study, a rule class may be a particular class of simple rules or the collection of all simple rules (all 12 classes of rules). There are another three dimensions in this class: memory span m, review span r, and performance measure. The memory span specifies the period of time for evaluating the rule performance. The review span indicates how often an investor evaluates the performance and switches the trading rule accordingly. We set $r \leq m$. We consider three performance measures: (1) the sum of m daily returns; (2) the average of m log daily returns; (3) the average log returns of all position-held days in the past m days. If there are more than two rules that generate equivalent returns, the investor is set to follow the one that performs better in the previous evaluation. There are $1,404$ strategies in the LS class; the details of the parameter values of this class are explicated in Appendix A.6.

The strategies of the VS class are based on the "voting" result of the trading rules in a rule class. In particular, each rule has one vote based on its suggested position. In our study, we consider two types of ballot: two-choice ballot for long and short positions and three-choice ballot for long, no, and short positions. A position is initiated if that position receives a larger proportion of votes. For the rule class, we consider only 12 classes of simple rules but not the one consisting of all rules. This is to avoid the voting result being dominated by a class with a large number of rules. There are another two dimensions in this class: memory span m and review span r, as in the LS class. There are 888 strategies in the VS class; the parameter values of this class are given in Appendix A.7.

The strategies of the PCS class differ from those in the LS and VS classes in that they allow for non-integral positions. Typically, a trading rule or strategy issues a signal of a specific position. Edwards and Magee (1997, pp. 535–540) proposed using an "evaluation index" to determine how a position can be divided. In this study, the voting results of the VS class serve as the evaluation index. As there are two types of ballot, there are also two evaluation indices. Each index is the percentage of the winning votes, and the resulting position is that suggested by the winning votes. There are also 888 strategies in the PCS class; the parameter values are the same as those in the VS class (see A.7).

4 Empirical Results

4.1 Data

In our empirical studies, the trading rules and strategies discussed in the preceding section are applied to four main indices: DJIA, S&P 500, NASDAQ Composite, and Russell 2000. Our analysis is based on the daily returns computed using daily closing prices of these indices. This kind of study makes practical sense because the trading rules and strategies utilize only public information available after the market closes. Moreover, as these indices are the targets of numerous index funds, our results would be informative to those "big players."

The daily index data from 1989 through 2002 are provided by the Commodity System Inc. The in-sample period is from 1990 through 2000 with 2779 observations; the data of 2001 (248 observations) and 2002 (252 observations) are reserved for out-of-sample evaluation. The data of 1989 (252 observations) are only used to formulate rules and strategies in 1990 that require the information from previous year. This data set extends more than a decade and may mitigate potential data snooping to some extent (Lo and MacKinlay, 1990; STW). Note that the volume data of DJIA are the share volumes of 30 stocks in DJIA; the volume data for NASDAQ Composite are the total share volume in NASDAQ. Because the exact share volume of S&P 500 is not available, we use the total share volume of New York Stock Exchange (NYSE) as a proxy because S&P 500 stocks amount more than 3/4 of the market capitalization in NYSE. For Russell 2000, since neither the exact volume data nor an appropriate proxy is available, we exclude the rules and strategies that require the information on volume. Therefore, there are only $35,776$ rules and strategies for testing Russell 2000.

4.2 Implementing White's Reality Check

We apply White's Reality Check to the rules and strategies in our expanded universe based on two performance criteria: mean return and Sharpe ratio. It must be mentioned that the rules in the HS, TA, RA, DTB and BTB classes generate much less trading signals than do the other trading rules during the sample period. The resulting mean returns and Sharpe ratios therefore may not be directly comparable with the results of other rules. As such, we adopt a modified approach to computing the returns of these five classes: the investor holds double positions when there is a long signal, one position when there is no signal, and no position when a short signal is issued.[2]

The Reality Check statistic $\overline{V}_n$ is computed according to (2), where $n = 2,779$ for in-sample evaluations. To compute the Reality Check p-values, 1000 bootstrapped samples are obtained by resampling the $n \times M$ return matrix $\{\eta_{k,t} = y_t s_{k,t-1}\}$, $t = 1, \dots, n$, $k = 1, \dots, M$. Each resampled return matrix is computed as follows.

1. Randomly select a row $(\eta_{t,1}, ..., \eta_{t,M})$ of the original return matrix as the first resampled row $\eta^*_{1,1}, ..., \eta^*_{1,M}$.

2. The second resampled row $(\eta^*_{2,1}, ..., \eta^*_{2,M})$ is randomly selected from the original return matrix with probability q, or it is set to the next row of the previously resampled row, i.e., $(\eta_{t+1,1}, ..., X_{t+1,M})$, with probability 1-$q$.[3]

3. Repeat the second step to form an $n \times M$ resampled return matrix.

From the j-th resampled return matrix, it is easy to compute $\bar{f}^*_k(j)$ and hence $\overline{V}^*_n(j)$ in (3). The significance of $\overline{V}_n$ is determined by the empirical distribution of $\overline{V}^*_n$.

In this study, all programs were written in S-plus 2000. To verify our programs, we follow the setting in STW and check the best rules, their mean returns, and the Reality Check p-values using the data in two periods: 1987–1996 and 1988–1996. The results are very close to theirs. We also conduct checks based on Brock, Lakonishok, and LeBaron (1992) and get similar outcomes. Similar to STW, we found that the probability parameter $q = 0.01, 0.1$, and 0.5 in stationary bootstrap yield similar results. We therefore report only the results under $q = 0.01$.

4.3 Profitable Rules and Strategies

We first find that, for the data from 1990 through 2000, profitable trading rules and strategies do exist for NASDAQ Composite and Russell 2000 but not for DJIA and S&P 500. We summarize the best rules and their p-values in Table 2 based on mean returns and Sharpe ratios. Note that throughout this study, the significance level in Reality Check is 1%.

[2] We are indebted to A. Timmermann for helpful suggestions on this issue.

[3] We adopt "wrap-up" resampling such that the first row $(\eta_{1,1}, ..., \eta_{1,M})$ is treated as the next row of the last row $(\eta_{n,1}, ..., \eta_{n,M})$ in resampling.

Table 2: Annual returns and Sharpe ratios of the best rules and strategies in 1990–2000.

Index	Best Rule (Strategy)	Annual Returns	Best Rule (Strategy)	Annual Sharpe ratio
DJIA	MSV[a]	14.67% (0.39)	PCS in OBV[e]	1.31 (0.27)
S&P 500	Contrarian OBV[b]	15.38% (0.22)	PCS in OBV[f]	1.19 (0.36)
NASDAQ	2-day MA[c]	38.19% (0.00**)	2-day MA[c]	1.96 (0.00**)
Russell 2000	2-day MA[d]	47.10% (0.00**)	2-day MA[c]	2.71 (0.00**)

Notes: Numbers in parentheses are Reality Check p-values; $**$ labels significance at 1% level.

a: Momentum strategy in volume based on a moving average oscillator: 5-day moving average of 250-day ROC, 20% overbought/oversold rate, and 50 fixed holding days;

b: 10–5 day cross MA;

c: MA rule with multiplicative band 0.001;

d: simple MA rule without multiplicative band;

e: Position changeable strategy based on the OBV class: 250-day memory span, 125-day review span, and three-choice ballot;

f: Position changeable strategy based on the OBV class: 250-day memory span, 250-day review span, and two-choice ballot.

From Table 2 we can see that, in terms of mean returns, the best rules for DJIA and S&P 500 are, respectively, a momentum strategy in volume and a contrarian rule in the OBV class. Neither of these rules yields statistically significant return based on the Reality Check p-values.[4] The same conclusion also holds when the performance measure is Sharpe ratio. On the other hand, the profits of the best rules for NASDAQ Composite and Ruseell 2000 are statistically significant at 1% level. For the former, the best rule is the 2-day MA rule with 0.001 multiplicative band, yielding average daily return 0.00152 (or 38.19% annually); for the latter, the best rule is the 2-day simple MA rule that gives average daily return 0.00186 (or 47.1% annually). In terms of Sharpe ratio, the best rules for NASDAQ Composite and Ruseell 2000 are also the 2-day MA rule with 0.001 multiplicative band. This rule yields the daily Sharpe ratios 0.1084 (1.96 annually) and 0.1923 (2.71 annually) for NASDAQ Composite and Russell 2000, respectively. It is noteworthy that the best rules for NASDAQ Composite and Russell 2000 are both short-

[4]For DJIA, the best rule yields the average daily return 0.00058 (or 14.67% annually). For S&P 500, the best rule gives the average daily return 0.00061 (or 15.38% annually).

term MA rules. This is consistent with STW's finding for DJIA in 1915–1996, where the best rules were also found to be short-term (2-day or 5-day) MA rules.

We summarize the top 10 rules and strategies that generate significant returns in Table 3. It can be seen that there are 6 investor's strategies for NASDAQ Composite and 8 for Russell 2000; these strategies are all learning strategies. In particular, the second and third best rules for NASDAQ Composite are, respectively, the learning strategy based on the MSV class and the learning strategy based on the collection of all rules. For Russell 2000, the second and third best rules are both the learning strategies based on the MA class. The average daily returns of these strategies are close to those of the best rules. It is interesting to note that learning strategies may outperform the simple rules that are used to construct these strategies. For example, the 5th best rule for NASDAQ Composite is a learning strategy based on the OBV class, yet it outperforms all simple OBV rules (the best OBV rule is the 9th best among all rules). Also, the 7th and 8th best rules for Russell 2000 are learning strategies based on the FR class but outperform simple filter rules.

We also summarize the number of rules and strategies that yield significant mean returns in Table 4. From this table we observe the following. First, most of profitable rules and strategies for NSADAQ Composite and Russell 2000 are based on filter rules and moving averages rules. Second, no contrarian rule is significantly profitable. Third, there are much more profitable investor's strategies than simple rules (27 strategies vs. 6 simple rules for NASDAQ Composite and 161 vs. 35 for Russell 2000). In fact, the profitable investor's strategies are all learning strategies. A complete table summarizing all profitable rules and strategies is available upon request. Fourth, and more interestingly, there exist profitable strategies based on non-profitable simple rules. For example, no simple momentum strategy in volume is profitable for NASDAQ Composite, but there are 7 profitable investor's strategies constructed from this class of rules. For Russell 2000, profitable strategies can also be constructed from the classes of support and resistance, channel break-outs and momentum strategies in price, even though there is no profitable simple rule in these classes.

The fourth finding above further strengthens what we have observed from Table 3: investor's strategies may improve on the profits of the simple rules on which they are

Table 3: Top 10 rules and strategies and their average daily returns in 1990–2000.

NASDAQ Composite		Russell 2000	
Rules (Strategies)	Daily Returns	Rules (Strategies)	Daily Returns
simple-MA	0.001516	simple-MA	0.001864
LS-MSV	0.001510	LS-MA	0.001775
LS-all	0.001508	LS-MA	0.001775
LS-MSV	0.001476	simple-MA	0.001756
LS-OBV	0.001458	LS-MA	0.001749
LS-MA	0.001453	LS-MA	0.001749
LS-MA	0.001453	LS-FR	0.001749
simple-MA	0.001448	LS-FR	0.001749
simple-OBV	0.001448	LS-MA	0.001736
simple-OBV	0.001435	LS-MA	0.001736

Notes: We list only the class titles of the rules and strategies but not their parameter values (details of the best rules are given in Table 2). For example, simple-MA stands for a simple rule in the MA class; LS-MA stands for a learning strategy based on the MA class. Note that LS-all is a learning strategy based on the collection of all 12 classes of simple rules.

based. An implication of this finding is that the profitability of technical analysis can not be evaluated solely based on simple rules. Technical investors are able to make higher and significant profits by intelligently utilizing the information from available simple rules. After all, it is the investor, not the simple rule, who makes trading decisions. This may also explain why technical analysis remains vivid in financial markets even when the profitability of simple rules are rejected in some empirical studies.

4.4 Comparison with the Buy-and-Hold Strategy

To confirm the profitability of technical analysis, we compare the returns of the best rules identified in the preceding subsection with that of the buy-and-hold strategy. Many studies had carried out such comparison, e.g., Fama and Blume (1966), Jensen and Benington (1970), Sweeney (1986, 1988), Levich and Thomas (1993), and Fernandez-

Table 4: Summary of significantly profitable rules and strategies in 1990–2000.

Class	NASDAQ Composite			Russell 2000		
	Simple Rules	Contrarian Rules	Investor's Strategies	Simple Rules	Contrarian Rules	Investor's Strategies
FR	2	0	2	22	0	50
MA	2	0	14	13	0	50
SR	0	0	0	0	0	7
CB	0	0	0	0	0	5
OBV	2	0	2	0	0	0
MSP	0	0	0	0	0	7
MSV	0	0	7	0	0	0
LS-all	N/A	N/A	2	N/A	N/A	42
Total	6	0	27	35	0	161

Notes: We list only the classes of significant profitable rules and investor's strategies, where LS-all is the class of learning strategies based on the collection of all 12 classes.

Rodriguez et al. (2000). It is quite surprising to note that such comparisons were usually made without taking transaction costs into account. As we find that the best rules for NASDAQ Composite and Russell 2000 are short-term rules, the transaction costs resulted from frequent trading should not be overlooked. Without transaction costs, the profits of technical trading rules may not be reliable, as discussed in Bessembinder and Chan (1998). We therefore also consider transaction costs in evaluating the returns of the best rules identified in the preceding section.

The exact transaction costs of large institutional investors are difficult to measure after the deregulation in 1970s. Fama and Blume (1966) used the floor trader cost as the minimal transaction cost, which is estimated as 0.05% for each one-way trade. Whether this cost rate is completely appropriate is still debatable. While Sweeney (1988) argues that this rate is overstated for the market after 1976, the other studies indicate the opposite. For example, Chan and Lakonishok (1993) estimate the commission cost for institutional traders in the largest decile of NYSE to be 0.13%. Knez and Ready (1996) also obtain similar estimates for the average bid-ask spread actually paid in one-way trades for Dow Jones securities. In this paper, we follow Fama and Blume (1966) and deduct 0.05% from transaction price for each one-way trade. Such a cost rate is applicable for market-makers and may also be possible for large institutional investors.[5]

We summarize the comparison results in Table 5. When there is no transaction cost, it can be seen that the best rule for NASDAQ Composite outperforms the buy-and-hold strategy in all in-sample periods except 1998 and 1999 (the best rule nevertheless generates positive profit in these two years). The best rule for Russell 2000 also results in higher returns in all 11 years. When transaction costs are taken into account, the best rule for NASDAQ Composite has superior performance only in 7 out of 11 in-sample periods, yet the best rule for Russell 2000 still dominates in all in-sample periods. In terms of the average return over 11 years, the best rules for both indices beat the buy-and-hold strategy, regardless of the presence of transaction costs. In out-of-sample periods 2001 and 2002, the buy-and-hold strategy yields large negative annual returns for both indices, except for Russell 2000 in 2001 where the annual return (1%) is barely positive. The best rule for NASDAQ Composite outperforms the buy-and-hold strategy, with positive returns in 2001 and smaller negative returns in 2002. The best rule for Russell 2000, on the other hand, generates larger positive returns in 2001 but larger negative returns in 2002. Although the best rules do not uniformly dominate the buy-and-hold strategy in all periods, it is fair to say that the best rules developed in-sample compare favorably with the buy-and-hold strategy in both in- and out-of-sample periods.

5 Conclusions

In this study, we follow STW to re-examine the profitability of technical analysis but consider a more complete set of trading rules and strategies. Using White's Reality Check, we find that significantly profitable simple rules and investor's strategies are available for the samples of relatively "young" markets (NASDAQ Composite and Russell 2000) but not for those of more "mature" markets (DJIA and S&P 500). Comparing with the buy-and-hold strategy, it is found that such profitable rules can generate higher returns

[5]Nevertheless, it is understood that this cost is underestimated for non-floor traders because other costs, such as brokerage commissions and bid-ask spreads, are inevitable. We are indebted to C. Jones and B. Lehmann for helpful discussions on this point.

Table 5: Annual returns of the best rules and the buy-and-hold strategy.

Year	NASDAQ Composite			Russell 2000		
	Best Rule w/o TC	Best Rule with TC	Buy-and-Hold	Best Rule w/o TC	Best Rule with TC	Buy-and-Hold
1990	67.6%	58.6%	−17.8%	53.7%	44.3%	−21.5%
1991	66.3%	56.6%	56.9%	68.0%	58.6%	43.7%
1992	35.1%	25.0%	15.5%	37.7%	27.7%	16.4%
1993	40.6%	30.8%	14.8%	47.9%	39.2%	17.0%
1994	33.2%	23.7%	−3.2%	41.4%	31.2%	−3.2%
1995	42.1%	32.4%	39.9%	38.4%	29.7%	26.2%
1996	40.9%	30.3%	22.7%	30.1%	19.7%	14.8%
1997	56.4%	45.8%	21.6%	52.4%	43.1%	20.5%
1998	27.1%	15.9%	39.6%	82.7%	72.9%	−3.4%
1999	8.9%	−3.1%	85.6%	34.5%	23.5%	19.6%
2000	3.1%	−8.7%	−39.3%	31.5%	19.8%	−4.2%
11-yr avg	38.2%	27.9%	21.5%	47.1%	37.2%	11.4%
2001	27.9%	18.1%	−21.7%	21.4%	11.7%	1.0%
2002	−22.3%	−32.4%	−41.2%	−34.4%	−44.0%	−21.7%

Notes: w/o TC: without transaction costs; with TC: with transaction costs; 11-yr avg: the average annual return of 11 years of the in-sample period; 2001 and 2002 are out-of-sample periods.

even when transaction costs are taken into account. These findings are consistent with Siegel (2002, pp. 290–297), and they may be used to support the claim that weak market efficiency has not yet formed in those "young" markets. Another interesting finding of our study is that technical investors are capable of constructing superior strategies from simple rules. Investor's strategies may improve on the profits of simple rules and even generate significant profits from unprofitable simple rules. This result shows that merely rejecting the profitability of simple trading rules does not necessarily negate the usefulness of technical analysis. Investor's strategies are indispensable elements in technical analysis and should not be ignored.

After completing this paper, we are aware the recent works of Peter R. Hansen.

In particular, Hansen (2004) points out that the null hypothesis (1) is an inequality constraint and that White's Reality Check is a test based on the least favorable configuration to the alternative. This property affects the asymptotic distribution, and the Reality Check test would be less powerful if there are many irrelevant alternatives models (rules). Nonetheless, we are able to reject the null (find significantly profitable rules) for NASDAQ Composite and Russell 2000 in our empirical study. These results are thus likely to be further confirmed (rather than reversed) even if the test of Hansen (2004) were used. On the other hand, our finding of no profitable rules for DJIA and S&P 500, as in STW, may be due to power deficiency of White' Reality Check. It would be very interesting to re-examine the profitability of technical analysis using Hansen's test. This is a future research direction.

Appendix A: The Parameter Values of the Trading Rules and Strategies

A.1 Momentum Strategies in Price and in Volume

The parameters of the momentum strategies are:

m (m-day ROC) = 2, 5, 10, 20, 30, 40, 50, 60, 125, 250 (10 values);

w (w-day moving average) = 2, 5, 10, 20, 30, 40, 50, 60, 125, 250 (10 values);

k (overbought/oversold level) = 0.05, 0.10, 0.15, 0.2 (4 values);

f (fixed holding days) = 5, 10, 25, 50 (4 values).

There are 10 m values and hence 10 simple oscillators. There are 10 w values. Setting w less than or equal to m, we have 55 moving average oscillators. For cross-over moving average oscillators, there are 45 ratios of moving averages when $w_1 < w_2$. We set $m = w_2$ and compute the moving averages of w_2-day ROC. Thus, there are 45 cross-over oscillators. We also set the overbought/oversold levels k no higher than that recommended by Pring (1993, Chap. 3). We consider 4 fixed holding days (f), as in STW. The total number of rules in the MSP class is thus $(10 + 55 + 45) \times 4 \times 4 = 1,760$. Similarly, there are 1,760 rules in the MSV class.

A.2 Head-and-Shoulders

There are 6 parameters in the HS class. In addition to n, x and f that are clear from the text, there are 3 more parameters: k, r and d. An investor will not initiate a position until the closing price in following days falls below the right trough by a multiplicative constant k, known as multiplicative band. An investor will liquidate the short position when the the closing price in following days exceeds the right trough by a multiplicative constant r, known as the stoploss rate. The fixed liquidation price is the closing price that declines by an amount equal to d times the head-trough difference, where the head-trough difference is calculated as the difference between the head and the average of two troughs. The parameters of the HS class are:

n (days of each subperiod) = 5, 10, 20, 50 (4 values);

x (differential rate of shoulders or troughs) = 0.005, 0.01, 0.015, 0.03, 0.05 (5 values);

k (multiplicative band) = 0, 0.005, 0.01, 0.02, 0.03 (5 values);

f (fixed holding days) = 5, 10, 25, 50 (4 values);

r (stoploss rate) = 0.005, 0.0075, 0.01, 0.015 (4 values);

d (parameter for fixed liquidation price) = 0.25, 0.5, 0.75, 1 (4 values).

Given 4 values of n, 5 values of x, and 5 values of k, there are 100 combinations of (n, x, k), and for each combination, there are 12 liquidation methods. The total number of rules in the HS class is thus $100 \times 12 = 1,200$.

Note: Lo, Mamaysky, and Wang (2000) recommended the differential rate $x = 0.015$; Edwards and Magee (1997, p. 81) recommended the multiplicative band $k = 0.03$; Chang and Osler (1999) recommended the stoploss rate $r = 0.005, 0.01$ and the fixed liquidation price parameter $d = 0.25$. These parameter values are all included in our setup.

A.3 Triangle

There are 5 parameters in the TA class. The parameters n, x, f and r are as in the HS class. The trend filter $x = 0$ means a position will be initiated upon completing a triangle. The investor will liquidate his/her position after the buy or sell signal lasts for d days; the values of d are set as STW. The parameters of the TA class are:

n (days of each subperiod) = 5, 10, 20, 50 (4 values);

x (trend filter) = 0, 0.001, 0.003, 0.005, 0.0075, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1 (15 values);

f (fixed holding days) = 5, 10, 25, 50 (4 values);

r (stoploss rate) = 0.005, 0.0075, 0.01, 0.015 (4 values);

d (day filter) = 2, 3, 4, 5 (4 values).

Given 4 values of n and 15 values of x, there are 60 combinations of (n, x), and for each combination, there are 12 liquidation methods. The total number of rules in the TA class is $60 \times 12 = 720$.

A.4 Rectangle

There are 6 parameters in the RA class. The parameters n, x, f, r and d are as in the TA class. The parameter that determines whether the tops (bottoms) are near a horizontal line is k (so that the bounds are $\pm k$). The parameters of the RA class are:

n (days of each subperiod) = 5, 10, 20, 50 (4 values);

k (parameter of bounds) = 0.005, 0.0075, 0.01 (3 values);

x (trend filter) = 0, 0.001, 0.003, 0.005, 0.0075, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1 (15 values);

f (fixed holding days) = 5, 10, 25, 50 (4 values);

r (stoploss rate) = 0.005, 0.0075, 0.01, 0.015 (4 values);

d (day filter) = 2, 3, 4, 5 (4 values).

Given 4 values of n, 3 values of k, and 15 values of x, there are 180 combinations of (n, k, x), and for each combination, there are 12 liquidation methods. The total number of rules in the RA class is $180 \times 12 = 2,160$.

A.5 Double Tops and Bottoms

There are 7 parameters in the DTB class. The parameters x, f, r and d are similar to those in the RA class. Following Lo, Mamaysky, and Wang (2000), each subperiod (n) is at least 20-day (about 1 month). The parameter of bounds k determines whether the tops (bottoms) are approximately equal; that is, each top (bottom) does not differ from the average of two tops (bottoms) for more than $\pm k$. For the gap rate g, the minimal (maximal) closing price of the second subperiod is below (above) the average of two tops (bottoms) with range g. Note that Edwards and Magee (1997) recommended the gap rate g to be 0.15–0.2 (pp. 159–160) and the trend filter x to be 0.03 (p. 161). The parameters of the DTB class are:

n (days of each subperiod) = 20, 40, 60 (3 values);

k (parameter of bounds) = 0.005, 0.01, 0.015, 0.03, 0.05 (5 values);

g (gap rate) = 0.1–0.15, 0.15–0.2, 0.2–0.25 (3 values);

x (trend filter) = 0, 0.01, 0.02, 0.03 (4 values);

f (fixed holding days) = 5, 10, 25, 50 (4 values);

r (stoploss rate) = 0.005, 0.0075, 0.01, 0.015 (4 values);

d (day filter) = 2, 3, 4, 5 (4 values).

There are 180 combinations of (n, k, g, x) and 12 liquidation methods. Thus, the total number of rules in the DTB class is $180 \times 12 = 2,160$.

A.6 Learning Strategies

There are 13 rule classes (12 classes of simple rules and the collection of all rules) and 3 performance measures. The other parameters of the LS class are:

m (memory span) = 2, 5, 10, 20, 40, 60, 125, 250 days (8 values);

r (review span) = 1, 5, 10, 20, 40, 60, 125, 250 days (8 values).

As $r \leq m$, there are 36 combinations of (m, r). The total number of strategies in this class is $13 \times 3 \times 36 = 1,404$.

A.7 Vote Strategies

The parameters of the VS class are:

m (memory span) =1, 2, 5, 10, 20, 40, 60, 125, 250 days (9 values);

r (review span) = 1, 5, 10, 20, 40, 60, 125, 250 days (8 values).

Given that $r \leq m$, there are 37 combinations of (m, r). With 12 rule classes and 2 types of ballots, the total number of strategies in this class is $12 \times 2 \times 37 = 888$.

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