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 test their profitability on the daily returns of four main indices from both relatively mature and young markets. It is found that profitable simple trading rules and investor's strategies do exist with statistical significance for NASDAQ Composite and Russell 2000 but not for DJIA and S&P500. Furthermore, the best rules for NASDAQ Composite and Russell 2000 outperform the buy-and-hold strategy with covered transaction costs in both in- and out-of-sample periods. Our results thus support the claim that the degree of market efficiency is related to market maturity.

Keywords: data snooping, market efficiency, stationary bootstrap, trading rules, technical analysis, 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 various trading rules and strategies to generate buy and sell signals. As these trading techniques are rather mechanical, whether they can generate 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), Neely, Weller, and Dittmar (1997), Brown, Goetzmann, and Kumar (1998), Rouwenhorst (1998), Neely and Weller (1999), Gencay (1996, 1998, 1999), Allen and Karjalainen (1999), Chang and Osler (1999), Lo, Mamaysky, and Wang (2000), and Chan, Hameed, and Tong (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 et al. (1992) raised a concern about the data snooping bias that may arise in 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., Bass (1999), 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&P500 index, and S&P500 futures. This method has also been applied by Sullivan et al. (2001) to demonstrate that the well known calendar effect is in fact a statistically insignificant phenomenon.

It may still be too early to declare the obituary for technical analysis. To properly quantify the effect of data snooping, White's Reality Check requires constructing a "full universe" of trading rules (STW, p. 1649). To this end, STW considered a total of 7846 trading rules drawn from a wide collection of commonly used rules in financial markets. Although 7846 is a large number, this collection of rules is far from a "full universe." First, several well known trading rules, such as head-and-shoulders and momentum strategies, were not included. Second, STW considered only simple trading rules but ignored investor's strategies. In practice, an investor need not stick to only one simple rule and may employ complex trading strategies, depending on his/her learning and decision making processes. Taking these rules and strategies into consideration should be able to expand the "effective span" of trading rules to a large extent and hence may affect the result of Reality Check. Moreover, STW studied only the samples from more "mature" markets. 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 from 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 the "universe" of 39,832 trading rules and strategies, including 18,326 simple trading rules, 18,326 corresponding "contrarian" rules, and 3,180 investor's strategies, such as the learning, vote, and position change strategies. Second, our study covers four main indices: DJIA, S&P500 index, NASDAQ Composite index, and Russell 2000 index. It is found that profitable simple trading rules and investor's strategies do exist with statistical significance for NASDAQ Composite and Russell 2000, yet the claims of STW and White (2000) still stand for DJIA and S&P500, even with the expanded universe. Furthermore, the best rules for NASDAQ Composite and Russell 2000 outperform the buy-and-hold strategy with covered transaction costs in both in- and out-of-sample periods. These results support the claim that the degree of market efficiency is related to market maturity. It is also worth noting that some investor's profitable strategies are based on unprofitable rules. That is, even simple trading rules alone may not be profitable, they may be intelligently utilized by technical investors to make profit.

This paper is organized as follows. White's Reality Check is discussed in Section 2. The trading rules and strategies of the expanded collection are described in Section 3. Section 4 presents the empirical results. Section 5 concludes the paper.

2 White's Reality Check

Data snooping is quite common in the empirical economic studies. As most of economic activities in the real world are not experimental, researchers may have little choice but relying on the same data set. In testing a model on a given data set, the data snooping bias arises when the results of previous tests on other models using the same data set are ignored. Lo and MacKinlay (1990) showed that even slight prior information may affect the statistical inferences dramatically.

In the literature, there are basically two different approaches to tackling the data snooping bias. The first approach mainly relies on data. When new data are not available, it is suggested to adopt a very large data set and validate the test using several subsamples; see e.g., Brock et al. (1992), Rouwenhorst (1998, 1999), Gencay (1998), Fernandez-Rodriguez et al. (2000). Sample splitting is, however, somewhat arbitrary and hence may lack desired objectivity. A more formal approach is to properly control the test size. This is done by considering all possible models and treat the current test as a test on the joint hypothesis so that the type I error can be properly controlled. For example, Lakonishok and Smidt (1988) proposed using the Bonferroni inequality to bound the test size. This method is, however, not appropriate when the number of hypotheses being tested is large, as in the case of testing the profitability of technical analysis. White's Reality Check proposed by White (2000) does not suffer from this problem.

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

$$H_0\colon \max_{k=1,\ldots,\ell} \mathbf{E}(f_k) \leq 0.$$

Clearly, if the null hypothesis is rejected, there exists at least one model (rule) that outperforms the benchmark. Testing this hypothesis is cumbersome when ℓ is large and when the models (rules) being tested are highly correlated with each other. It is then natural to base a test on the maximum of the normalized sample average $\bar{f}_k$:

$$\overline{V}_\ell = \max_{k=1,\ldots,\ell} \sqrt{n}\, \bar{f}_k,$$

where n is the number of sample observations. White (2000) suggested using the stationary bootstrap method proposed by Politis and Romano (1994) to compute its p-values.[1]

Specifically, let $f^*_{k,i}$ $(i = 1, \ldots, B)$ denote the i-th bootstrapped sample of f_k and $\bar{f}^*_{k,i}$ its sample average. We then obtain the following realizations:

$$\overline{V}^*_{\ell,i} = \max_{k=1,\ldots,\ell} \sqrt{n}(\bar{f}^*_{k,i} - \bar{f}_k), \qquad i = 1, \ldots, B.$$

White (2000, Proposition 2.2) showed that, as n tends to infinity,

$$\max_{k=1,\ldots,\ell} \sqrt{n}[\bar{f}_k - \mathbf{E}(f^*_k)] \Rightarrow V_\ell \equiv \max_{k=1,\ldots,\ell} Z_k,$$

[1] In addition to the bootstrap method, White (2000) also proposed using Monte Carlo simulations to compute the p-values. We discuss only the latter because it is computationally more efficient when there is a large set of models.

where $Z_k \sim N(0, \Omega)$ with Ω a positive semi-definite matrix, and $\Rightarrow$ denotes convergence in distribution. It is also shown in Corollary 2.4 of White (2000) that the empirical distribution of $\overline{V}_\ell^*$ (constructed from the realizations $\overline{V}_{\ell,i}^*, i = 1, \ldots, B$) is asymptotically equivalent to the distribution of $\max_{k=1,\ldots,\ell} \sqrt{n}[\bar{f}_k - \mathbf{E}(f_k^*)]$. Thus, the Reality Check p-value can be obtained by comparing the test statistic $\overline{V}_\ell$ with the quantiles of the empirical distribution of $\overline{V}_\ell^*$. The null hypothesis is rejected whenever the p-value is less than a given significance level.

3 An Expanded Set of Trading Rules and Strategies

In this study, we consider an expanded set of technical trading techniques, including simple trading rules, contrarian rules, and investor's strategies. This set is more complete than that of STW. Table 1 is a summary of all rules and strategies considered in this study.

(Table 1 Here)

3.1 Simple Trading Rules

There are 12 classes of simple trading rules in our expanded set of trading rules an strategies. These rules are well known among market professionals, including filter rules, moving average, support-and-resistance, channel break-outs, on-balance volume averages, momentum strategies, head-and-shoulders, broadening tops and bottoms, triangle, rectangle, and double tops and bottoms. Total 18,326 rules from these 12 classes are analyzed in this study. Though some previous studies have considered more than one class of simple trading rules (e.g., BLL (1992), STW (1999), LMW (2000)), the proposed set here covering 12 most important rule classes is much larger. Similar to most studies, the time span of information used in trading rules is limited within one year.

Class 1 to class 5 are replicates of STW (1999)'s universe of 7,846 simple trading rules, in which our programming and setting follow the descriptions of STW. They are filter rules (FR), moving averages (MA), support-and-resistance (SR), channel break-outs (known as Dow theory) (CB), and on balance volume averages (OBV).

On momentum strategies (MS), we consider momentum strategies in price (MSP) as class 6 and the momentum strategies in volume (MSV) as class 7.[2] The momentum measure used in this study is the rate of change (ROC) (Pring (1991), Ch. 3 and 4, LeBaron (1991), DeMark (1994), Ch. 10, White (2000)). In each day, the m-day ROC means the value that the current closing price (volume) minuses the m-day past closing price (volume) and is then divided by the m-day past closing price (volume). Pring (1991, Ch. 18, 1993) recommended three momentum oscillators: Simple oscillator, moving average oscillator, and cross-over moving average oscillator. The simple oscillator is exactly the ROC, and the moving average oscillator is the moving average ROC. The cross-over moving average oscillator is the value of a shorter moving average ROC divided by a longer moving average ROC. A overbought/oversold level is designed to determine when to initiate a position: once the oscillator moves up across the overbought level, it is a signal for investors to initiate a long position. On the other hand, while the oscillator moves down across the oversold level, it is a signal for investors to initiate a short position. After initiating a position, the investor is set to hold the position with fixed holding days and then liquidate it. The details of MSP and MSV are described in Appendix A.1. There are total 3,520 MS rules: 1,760 rules in MSP class and 1,760 rules in MSV class.

Class 8 is the head-and-shoulders (HS). When implementing the search process for HS and invert HS (IHS) patterns, we divide a sample period into five equal subperiods and see if the price movements in these subperiods form left shoulder, left trough, head, right trough, and right shoulder respectively. The IHS pattern can be simply considered as a reversed pattern of the HS. Once the HS (IHS) pattern is completed, future price movement is expected to largely decline (ascend) because the falling (rising) power in the market is believed to "win out" through a long struggle. So when the HS (IHS) forms, it is a signal to investors for taking short (long) position. Finally, we considered three liquidation methods: fixed holding days, stoploss rate, and a fixed liquidation price. The details of the HS are explicated in Appendix A.2. There are 1,200 rules in HS class.

The triangle (TA), as the class 9, requires a series of continuous top-and-bottom patterns which converges to a triangular pattern. In identifying the TA, we divide a sample period into five equal subperiods, orderly numbered 1 to 5 in time. There are two definitions of the TA: First, the maxima of subperiod 1, 3, and 5 are tops, and

[2] In the literature, there are three types of "momentum," including price momentum, earnings momentum (Chan, Jegadeesh, and Lakonishok (1996 and 1999)) and volume momentum (Chan, Hameed, and Tong (2000)). We did not consider earnings momentum because we examine market indexes, not individual stocks.

the minima of subperiod 2 and 4 are bottoms. Second, the minima of subperiod 1, 3, and 5 are bottoms, and the maxima of subperiod 2 and 4 are tops. In both cases, the convergence pattern requires the subsequent tops decreasing and the subsequent bottoms increasing. The rectangle (RA), as the class 10, consists of a sequence of local extrema that forms a track with horizontal upper boundary and lower boundary. In a sample period comprised of five subsequent equal subperiods orderly numbered 1 to 5, the RA has two definitions: First, all the tops of odd subperiods lie near a upper horizontal line and all the bottoms of even subperiods lie near a lower horizontal line. Second, all the tops of even subperiods lie near a upper horizontal line and all the bottoms of odd subperiods lie near a lower horizontal line. Because the TA and RA may be either a reversal pattern or a consolidation pattern (Edwards and Magee (1997), p. 202), the future trend after the TA and RA can not be identified without more information provided by following price movement. That necessitates a trend filter for us to ensure the future trend after the formation of the TA and RA: after the TA or RA is completed, the closing price which ascend over the latest top by a trend filter x can be regarded as a sign of long position, and the closing price fall below the latest bottom by x can be considered as a sign of short position. Moreover, we considered three liquidation methods: fixed holding days, stoploss rate, and day filter. The details of TA and RA are explicated in Appendix A.3 and A.4. There are 720 rules in TA class and 2,160 rules in RA class.

The class 11 is the double top and bottom (DTB) which includes the double-top and double-bottom. In a sample period comprised of three subsequent equal subperiods, the double-top is formed by two equal tops (the maxima in subperiod 1 and 3) intercepted by one bottom (the minimum of subperiod 2), and the double-bottom is formed by two equal bottoms (the minima in subperiod 1 and 3) interposed by one top (the maximum of subperiod 2). The broaden top and bottom (BTB), as class 12, can be regarded as a converse pattern of the TA. It is established on five consecutive equal subperiods where the consecutive tops (bottoms) become higher and higher (lower and lower). Similar to TA and RA, DTB and BTB can be either a consolidation pattern or a reversal pattern, so we propose a trend filter to identify the trend after the DTB and BTB. After the DTB or BTB completes, if the closing price in a following day ascend over the latest top by a trend filter x, it can be regarded as a sign of long position; if the closing price falls below the latest bottom by x, it can be considered as a sign of short position. Similarly, we considered three liquidation methods: fixed holding days, stoploss rate, and day filters. The details of DTB and BTB are explicated in Appendix A.5 and A.6. There are 2,160 rules in DTB class and 720 rules in BTB class.

It is noted the latter five classes including HS, TA, RA, DTB and BTB are "rare" patterns because that the trade signals arouse by these classes occur much more scarcely than the first seven classes. Moreover, the sparse occurrence of the trade signals makes the the mean returns inequitable and the Sharpe Ratio invalid. Therefore, we conduct a modified approach in computing the returns of these five classes: the investor holds double positions while a long signal occurs, holds one position while there is no signal, and holds no position while a short signal occurs.[3]

3.2 Contrarian Rules

"Contrarian" operation frequently appeared in traders' biographies (e.g., Lewis (1989), p. 175; Bauer and Dahlquist (1999), p. 408; LeBaron and Vaitilingam (1999), Ch. 2, 25, and 28; Siegel, 2002, p. 330), and applying such strategy to technical analysis is worth of investigation. Traditional technical analysts thought that the occurrence of trading signals of some trading rules are caused by price deviating far from the current state, and can prognosticate the change in trend. However, such deviations might be a consequence of temporary abnormality, and the market will return to its original equivalence sooner or later.[4] We are motivated to inspect the true feasibility of such an unconventional approach in technical analysis.

Based on 18,326 simple trading rules, we can simply propose 18,326 corresponding contrarian rules in which the investor holds an inverse position according to the trading signals of the corresponding simple trading rules.[5] In the five rare classes of simple trading rules, a neutral position is still set to be 1, a long signal trigger a short position, and vice versa.

3.3 Investor's Strategies

In financial market, it is usually observed that many investors use same trading rules but some of them become winners while others become losers. Are those winners the lucky ones or the smart ones? We therefore doubt whether there exist truly gainful

[3]Unlike BLL (1992, p. 1741) and STW (1999, p. 1657), this approach does not consider the "borrow" and risk-free interest rate. In this part, the authors got helpful suggestions from personal communication with A. Timmermann.

[4]For example, Jegadeesh (1990) and Lehmann (1990) both found that the stock price is of negative serial correlation monthly and weekly. That suggests the profitability of contrarian operation since the investor may utilize the temporary abnormality in market to gain.

[5]The term "contrarian" rules used here is defined on the aspect of technical analysis, and is different from Lakonishok, Shleifer, and Vishny's (1994) term.

technical investors, even with no profitable rule, in the market. Although technical rules are informative, the final decision is made by the investors as Pring (1991), "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)." So, investor's strategies are even more important than simple trading rules because what really matter are investors, not rules. In spite of their importance, investor's strategies have not been deeply analyzed by previous studies. In this study, we consider the investor's strategies that mean the intelligent and adaptive processes of investors to make trading decision based on evaluating the previous performance of technical trading rules. We proposed three classes of investor's strategies, including learning strategies (LS), vote strategies (VS), position changeable strategies (PC). These strategies result in 3,180 rules.

Learning strategies (LS) are devoted to delineate the investor's learning behavior in switching his position by following the best-performed rule within all 18,326 simple trading rules. Moreover, the situation that the investor uses only one class of simple trading rules and follows the best-performed rule within that class is also considered. We use four dimensions to structure out the LS class: rule class, memory span, review span, and performance measure. Rule class, as described above, means the search range of the investor on all classes or on a single class of simple trading rules. Memory span (m) indicates the backward time span that the investor will record each rule's performance, and the review span (r) means how often an investor will switch the trading rule he follows. Three performance measures of profit are adopted: the first one is the cumulative returns that are the cumulative sum of previous m-day returns; the second one is the average log returns of past m days; the third one is the average log returns of all position-held days in past m days. Once more than two rules generate equivalent returns in previous m days, the investor is set to follow the rule that ranks prior in our rule combination in computation. The details of LS are explicated in Appendix A.7. There are total 1,404 strategies in LS class.

Vote strategies (VS) are also feasible to identify the future trend by considering the "vote" of multiple trading rules (e.g., Bass (1999), p. 207). On the vote strategies proposed in this study, the investor will conduct voting based on all rules within a rule class that he follows.[6] We considered an equal-weight (one rule has one vote) ballot process in two ballot types: the two-choice ballot (1:long or -1:short) and three-choice ballot (1:long, 0:neutral, or -1:short). In the two-choice ballot, the number of neutral

[6]The vote based on all 12 rule classes is not considered here because the rule number of every class, as the weight in vote, is neither identical nor comparable.

signals is excluded from vote, and the investor can take only long or short. In the three-choice ballot, the number of neutral signals is considered in vote, and the investor can take long, short, or out-of-market. Finally, the same as LS, memory span and review span are also included in VS. The details of VS are explicated in Appendix A.8. There are total 888 strategies in VS class.

Finally, we also consider the position changeable strategies (PC). Most previous studies based their conclusions on a common assumption that the investor can hold only and exactly one position — an inseparable unit — in every trading day. Although such a simple assumption helps researchers model the problem, it is over-simplified and ignores the situation that the investor can hold non-integral position by his confidence in future trend. Because it is somewhat difficult to make a clear cut between up and down trend in market perspective, Edwards and Magee (1997, pp. 535–540) proposed an "evaluation index" in allotting position instead of taking only one position. In an example of 100 stocks, if 75 stocks rise and else 25 fall, the evaluation index is 75% in bullish direction. In this study, we utilized the proposed VS as the counting basis of the evaluation index. Two types of evaluation index are used in corresponding to two ballot types. The first evaluation index is the value of the votes of winner in three-choice ballot divided by the total votes. The second evaluation index is the value of the votes of winner in two-choice ballot divided by all the non-zero votes. The investor holds a non-integral position in the same as the evaluation index that changes everyday. Similar to LS, the memory span and review span are considered. The details of PC are explicated in Appendix A.9. There are total 888 strategies in PC class.

4 Empirical Study

4.1 The Data

We examine the profitability of technical analysis in four main indexes in 1990–2000: Dow Jones Industrial Average (DJIA) index, S&P 500 index, NASDAQ composite index, and Russell 2000 index.[7] Indexes of 2001 and 2002 are considered as the out-of-sample to corroborate significantly lucrative rules existing in that period, and indexes of 1989 is only used for formulating rules and strategies which require at most one-year-before information. Since NASDAQ composite index is composite index weighted by each stock's

[7]Like most studies (Neftci (1991), BLL (1992), Gencay (1996 and 1998), STW (1999 and 2002), Allen and Karjalainen (1999), White (2000), Chan, Hameed, and Tong (2000), Siegel (2002), we evaluate the profitability of technical analysis on index returns.

market capital and Russell 2000 index covers the smallest 2,000 stocks of the top 3,000, the overlap of these two indexes is few and we can regard them as two different samples. In computing the returns, we consider "interday" technical rules, not "intraday" technical rules, which means each trading rule bases its prediction of future price on available daily information after the market closes. Investor follows the trading signals generated by technical rules to initiate and modify his position once a day under the assumption that every investor can use public information only (Sweeney (1988), White (2000)). Data are provided by the Commodity System Inc. (CSI). The data spanning across one decade help to prevent our examination from possible data snooping bias (Lo and MacKinlay (1990), STW (1999 and 2002)). The returns are calculated with daily closing prices.

It is reasonable for us to examine the profitability of technical analysis based on these main indexes because all these indexes can be replicated by investors (Siegel (2002), pp. 54–55, 294–297). Since these indexes are targets of numerous index funds, the profitability of technical analysis on these indexes makes sense to those "big players". But two further considerations left: the feasibility of short position and the dividend effect. The short positioning is widely available in recent stock markets, so it is valid to consider the short position used in this study. The dividend effect is somehow difficult to be considered in the price-weighted DJIA, but it can be well reflected in capital-weighted indexes like S&P 500, NASDAQ composite, and Russell 2000.

The volume data of DJIA and NASDAQ composite are the share volume of the DJIA 30 composite stocks and the total share volume in the NASDAQ, respectively. Because the exact share volume of S&P 500 is not available, we use the total share volume of New York Stock Exchange (NYSE) because S&P 500 stocks cover over 3/4 of the market capitalization. In Russell 2000 index, since neither the exact volume data nor an appropriate proxy is available, we preclude the rules and strategies involving volume in conducting Reality Check. Therefore, the total number of rules and strategies in the set of technical analysis for examining Russell 2000 is 35,776.

4.2 Implementing White's Reality Check

Two performance criteria, the mean returns and the Sharpe ratio, are used in Reality Check. Similar to STW (1999), the benchmark system is the neutral rule (i.e., out of market) in mean returns criterion, and is the daily risk-free interest rate in Sharpe ratio criterion. The details of Reality Check with these two performance criteria are described in Appendix B. The stationary bootstrap (Politis and Romano (1994)) is used in resampling the return series to conduct Reality Check (see Appendix C). The probability parameter of stationary bootstrap (q) is set to be 0.1.[8]

It is noteworthy that the null hypothesis of our testing here can be described as "Neither technical rule nor technical investor can beat the stock market," which is expansive than STW's (1999) null hypothesis "No technical rule can guarantee profits in the stock market."

4.3 Results in Mean Returns and Sharpe Ratio

The results of Reality Check with mean returns and Sharpe ratio in 1990–2000 are listed in Table 2 and 3 respectively. The results show there exist neither profitable trading rule nor gainful investor's strategy in DJIA and S&P 500. In Table 2, DJIA's best rule, as one of MSV class, carries 0.00058 mean returns daily (or 14.67% yearly) and provides 0.386 p-value in Reality Check. The best rule in S&P 500, belonging to contrarian OBV class, produces 0.00061 mean returns daily (or 15.38% yearly) and provides 0.219 p-value in Reality Check. So it is found that both the best rules of DJIA and S&P 500 are insignificant in mean returns under Reality Check. The same consequence occurs in Sharpe ratio as Table 3. STW (1999) and White (2000) concluded that DJIA and S&P 500 exist no profitable rule, and our empirical results corroborate their conclusion by using a more complete set of technical analysis.[9]

(Table 2 and 3 Here)

In contrast to the outcomes in DJIA and S&P 500, our results show that there exist significantly profitable rules and strategies in these two relatively young markets, the NASDAQ composite and Russell 2000.[10] The best-performed rule in NASDAQ composite, the 2-day MA with 0.001 multiplicative band, generates mean returns of 0.00152 daily (or 38.19% yearly), which is significant under Reality Check (Table 2). In Sharpe ratio, the best rule is exactly the same one and carries 0.1084 daily Sharpe ratio (or 1.96 annually) as Table 3. In Russell 2000, 2-day simple MA is the best rule in mean returns criterion and provides 0.00186 mean returns daily (or 47.1% annually), and the

[8] Like STW's (1999) results, we found that the results of $q = 0.01$, 0.1, and 0.5 is similar, so we present all our results in $q = 0.01$ only.

[9] It is noted that, even we have structured a more complete set, we still could not totally preclude the existence of specific profitable rules or investor's strategies which we neglect in constructing our set of technical analysis.

[10] We use 1% significance level in Reality Check throughout this study.

2-day MA with 0.001 multiplicative band is the best rule in Sharpe ratio criterion and produces 0.1923 daily Sharpe ratio (or 2.72 annually) as Table 2.[11] The outcome that, in NASDAQ composite and Russell 2000, the best rules in mean returns are similar to Sharpe ratio show the consistent advantage of superior rules in different performance criteria and in different data sets.

Furthermore, it is noteworthy that the best rules of NASDAQ composite and Russell 2000 belong to 2-day MA pattern. Our results are in accordance with STW's (1999) study that shows all the best rules are 2-day or 5-day MA rules in 1915–1996 under no transaction costs. Moreover, most profitable simple rules observed are short-term. Our study as well as STW (1999) suggest that, regardless of the transaction costs, short-term technical trading rules are better than long-term technical trading rules. However, the causes of such phenomenon is still unclear and requires further investigation.

Besides simple trading rules, investor's strategies are also ascertained to be truly profitable. With the summary of significantly profitable rules and strategies in 1990–2000 provided in Table 4, it is appealing that in NASDAQ composite, although there exists no profitable simple trading rule in MSV class, seven significantly gainful MSV-based LS strategies are found. The similar outcome occurs in Russell 2000, in which there exists no profitable simple trading rule in SR, CB and MSP classes, but 7 SR-based LS strategies, 5 CB-based LS strategies, and 7 MSP-based LS strategies are found with significance. Therefore, we substantiate the true merit of technical investor's selection: the investor strategies can really make profits even that their base rule class is unprofitable. The conjecture that there may exist no profitable rule but profitable investors is confirmed. That may also explain why these trading rules refuted by academic studies remain alive in stock markets: it is the technical investor who utilizes these technical rules to make profits.

(Table 4 Here)

[11] The results in two criteria are consistent: the second best rule in Sharpe ratio is 2-day simple MA (0.162 daily Sharpe ratio) and the second best rule in mean returns criterion is 2-day MA with 0.001 multiplicative band (0.00176 mean returns). Therefore, 2-day simple MA and 2-day MA with 0.001 multiplicative band can both be regarded as the best-performed rules in Russell 2000.

4.4 Buy-And-Hold Policy: A Benchmark

In some studies, the profitability of technical analysis is confirmed by comparing that to the profits of buy-and-hold policy (Fama and Blume (1966), Jensen and Benington (1970), Sweeney (1986 and 1988), Levich and Thomas (1993), Fernandez-Rodriguez, Gonzalez-Martel, and Sosvilla-Rivero (2000)), which assumes the investor holds a long position throughout all the sample period without other trading activities. However, stock markets are not sure to rise (Shiller (2000), p. 48), so the buy-and-hold policy does not serve as an appropriate benchmark system for the null hypothesis in Reality Check.[12] Here we provide a comparison between the returns of the best rules and buy-and-hold policy for 1990–2002 in Table 5. During the in-sample period 1990-2000, the best rule of NASDAQ composite (first column) outperforms the buy-and-hold policy (third column) in all times except 1998 and 1999, and the best rule of Russell 2000 outguesses the buy-and-hold policy throughout 11 years. In the out-of-sample period 2001 and 2002, both best rules still beat the buy-and-hold policy.

(Table 5 Here)

4.5 Consideration on Transaction Costs

Since Fama and Blume (1966), measuring transaction costs is also very crucial in verifying the profitability of technical analysis in stock market, especially for short-term trading rules. The exact transaction costs rate of large institute investors is especially difficult to measure after the deregulation in the 1970s. Fama and Blume (1966) used the floor trader costs as minimal transaction costs, which are estimated as 1/20 percent (0.05%) for each one-way trade. This cost rate is regarded as overstatement by Sweeney (1988) for the market circumstance after the 1976. But some other studies indicate this cost rate is underestimated. Chan and Lakonishok (1993) estimate the commissions costs for institutional traders in the largest decile of NYSE to be 0.13%. Knez and Ready (1996) estimate the average bid-ask spread actually paid in one-way trades for Dow Jones securities to be between 0.11% and 0.13%. Based on the argument of transaction costs,

[12] Although Neely, Weller, and Dittmar (1997) suggested that the buy-and-hold policy is a suitable benchmark in stock markets due to the growth in long trend, we could not share their viewpoint. The sudden downturn in NASDAQ composite in 2000 and the lasting depression of Nikkei index in the 90's are two overtly contractual examples.

Bessembinder and Chan (1998) suggest that the profitable results from technical trading rules are not so reliable. Many recent studies are devoted to estimate the propositional cost rate (e.g., Jones and Lipson (2001), Jones (2002)).

In this study, we examine the profitability as one-way floor-trader case and deduct 0.05% of returns whenever buy and sell occurs.[13] We recognize that, for those non-floor traders, other costs including brokerage commissions and bid-ask spreads are inevitable. But such a cost rate is applicable for market-makers, and is also possible for specific huge institutional investors.

Presented in Table 5 again, we observe that, while considering the transaction costs, the advantages of these two best rules still maintain in comparison with the buy-and-hold policy in most times, except for the NASDAQ composite in 1995, 1998, and 1999, and Russell 2000 in 2002. In some extreme years, the difference between best rules and buy-and-hold policy could be high as to over 50% (NASDAQ composite in 1990, Russell 2000 in 1990 and 1998), and once be negative about 90% for NASDAQ composite in 1999. Therefore, we regard the profitability of technical analysis as sustainable through our sample period with covering transaction costs.

5 Conclusions

In this study, we re-examine the profitability of technical analysis with considering White's Reality Check, buy-and-hold benchmark, as well as transaction costs. We study a larger and more complete set of technical analysis comprising of 39,832 simple trading rules, contrarian rules, and investor's strategies. The 18,326 simple trading rules we structure out covers STW's (1999) universe as a subset. Then we consider 18,326 contrarian rules that have never been investigated previously. Besides trading rules, we propose 3,180 investor's strategies to simulate the technical investor's behavior that was neglected in the literature. To avoid the data snooping bias, we apply White's Reality Check (White, 2000) to test four main market including DJIA, S&P 500, NASDAQ composite, and Russell 2000 in 1990–2002. The null hypothesis of our testing for the profitability argument is "Neither technical rule nor technical investor can beat the stock market."

In NASDAQ composite and Russell 2000, it is found that there exist truly profitable simple trading rules and investor's strategies. The best rule in NASDAQ composite, the 2-day MA with 0.001 multiplicative band, generates 38.2% returns and 1.96 Sharpe ratio.

[13]This method follows Siegel (2002, p. 291).

The best rule in Russell 2000, the 2-day simple MA, generates 47.1% annual returns and 2.67 Sharpe ratio. Since both best rules are significant in mean returns and Sharpe ratio under Reality Check, the profitability of simple trading rules is confirmed. When we take transaction costs into account and find that both best rules still surpass buy-and-hold policy in both markets in 1990–2002, with only few exception years. Moreover, regardless of transactions costs, almost all the best trading rules in this study and in STW (1999) are short-term rules. Such a common short-term advantage need further investigations to find inherent reasons.

Finally, the investor's strategies are found to be significantly profitable in NASDAQ composite and Russell 2000 in 1990–2000. Particularly, among all significantly profitable investor's strategies, some are based on rule classes that include no profitable rule at all. This outcome apprises us that an intelligent technical investor can really make profits even no profitable technical rules in his hand. This outcome also explains why there exist some successful technical investors who always make profits using commonplace and non-esoteric trading rules. It is preliminarily remarked that there exist not only profitable technical trading rules but also gainful technical investors in NASDAQ composite and Russell 2000 in this period. In contrast, neither trading rule nor investor's strategy is found to be lucrative in two mature markets, DJIA and S&P 500. On applying technical analysis, the heterogeneity in profitability between mature markets and relatively young markets is further confirmed. With Siegel (2002, pp. 290–297) and our findings, it therefore is reasonable for us to leave a concluding remark that, there exist both profitable technical rules and gainful technical investors in some relatively young markets where the weak market efficiency has not formed.

Appendix A: Detailed Descriptions of Our Expanded Set

A.1 Momentum Strategies (MS)

Momentum strategies include MS in price (MSP) and MS in volume (MSV). The parameters of MSP are set as follows:
m (m-day ROC) = 2, 5, 10, 20, 30, 40, 50, 60, 125, 250 (in days) (10 values);

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

k (overbought/oversold levels) = 5%, 10%, 15%, 20% (4 values);

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

The total number of MSP is $[m+55(m-w \text{ combinations})+45(\text{long} - \text{short combinations})] \times k \times f = 1,760$.
Note: w has to be less than or equal to m, so there are 55 $m-w$ combinations for moving average oscillator; In cross-over moving average oscillator, there are 45 long-short combinations from 10 values in w; Pring (1993, Ch. 3) recommended the overbought/oversold level (k) to be 20%; fixed holding days (f) are set as STW (1999). After initiating a position, the investor is set to hold the position with fixed holding days.

Following the same procedure of MSP, we develop 1,760 rules in MSV.

A.2 Head-and-Shoulders (HS)

The local length (n) determines the day number of five subperiods. Range of shoulders (troughs), x, restricts the differential rate between two shoulders (troughs) because two shoulders (troughs) need to be approximately equivalent. To make sure the formation of a trend, a multiplicative band (k) is considered. That is, the investor would not initiate a position till the closing price in following days ascend (fall) across the right trough with k rate. The meaning of fixed holding days (f) has been discussed previously. The stoploss rate (r) means the investor will liquidate the short (long) position when the price ascend (fall) across the right trough by r. The fixed liquidation price indicates the price is expected to fall (rise) to an expected price (d times the head-trough distance) (Chang and Osler (1999)). The head-trough distance is counted as the difference between the head and the average of two troughs.

There are still two requirements of the HS: first, the maximal price of head subperiod is required to the highest price of all five subperiods. Second, in head subperiod and shoulder subperiod, the minimal prices are required to be higher than that of adjacent trough subperiods. Contrarily, the maximal prices of two troughs are required to be lower than than that of neighbor head subperiod and shoulder subperiod. This requirement is important to make the found pattern more plausible in chart. The requirement of IHS can be easily induced by reverting the requirements above.

The parameters of HS are set as follows:

n (local length) = 5, 10, 20, 50 (in days) (4 values);

x (range of shoulders and troughs) = 0.005, 0.01, 0.015, 0.03, 0.05 (5 values);

k (multiplicative band) = 0.005, 0.01, 0.02, 0.03 (4 values);

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

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

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

The total number is $n \times x \times (1 + k) \times (f + r + d) = 1,200$.

Note: LMW (2000) recommended the range of shoulders and troughs (x) to be 0.015; Edwards and Magee (1997, p. 81) recommended the multiplicative band (k) to be 0.03; fixed holding days (f) are set as STW (1999); Chang and Osler (1999) recommended the stoploss rate (r) to be 0.005 and 0.01, and the fixed liquidation price parameter (d) to be 0.25.

A.3 Triangle (TA)

Generally, there are two definitions of the TA: first, the maximal closing prices of three odd subperiods (M_1, M_3, M_5 as tops) satisfy $M_1 > M_3 > M_5$, and the minimal closing prices of two even subperiods (m_2, m_4 as bottoms) satisfy $m_2 < m_4$. Second, the minimal closing prices of three odd subperiods (m_1, m_3, m_5 as bottoms) satisfy $m_1 < m_3 < m_5$, and the maximal closing prices of two even subperiods (M_2, M_4 as tops) satisfy $M_2 > M_4$. We include some extra criteria in our definition for a more accurate pattern: the minimal price of a top subperiod is required to be higher than that of adjacent bottom subperiod(s), and the maximal price of a top subperiod is required to be higher than than that of adjacent bottom subperiod(s).

The parameters of TA are set as follows:

n (local length) = 5, 10, 20, 50 (in days) (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 (in days) (4 values);
r (stoploss rate) = 0.005, 0.0075, 0.01, 0.015 (4 values);
d (day filter) = 2, 3, 4, 5 (4 values).

The total number is $n \times x \times (f + r + d) = 720$.

Note: 0 in the trend filter (x) indicates the investor take action immediately after the TA completes; Edwards and Magee (1997, p. 112) recommended the trend filter (x) to be 0.03; the fixed holding days (f) are set as STW (1999); the stoploss rate (r) is set as HS in Chang and Osler (1999); the day filter (d) is set as STW (1999).

A.4 Rectangle (RA)

Generally, there are two definitions of the RA: first, the maximal closing prices of three odd subperiods (M_1, M_3, M_5 as tops) all lie near a horizontal line (upper bound), and the minimal closing prices of two even local subperiods (m_2, m_4 as bottoms) all lie near a horizontal line (lower bound). Second, the closing prices of three odd subperiods (m_1, m_3, m_5 as bottoms) all lie near a horizontal line (lower bound), and the closing prices of two even subperiods (M_2, M_4) all lie near a horizontal line (upper bound). These tops (bottoms) are considered as "near a horizontal line" if they lie within a range of their average. In this study, we try three different ranges ($\pm 0.005, \pm 0.0075, \pm 0.01$). Moreover, similar to the requirements of the TA, 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 than that of adjacent bottom subperiod(s).

The parameters of RA are set as follows:
n (local length) = 5, 10, 20, 50 (in days) (4 values);
k (range of bound) = 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 (in days) (4 values);
r (stoploss rate) = 0.005, 0.0075, 0.01, 0.015 (4 values);
d (day filter) = 2, 3, 4, 5 (4 values).

The total number is $n \times x \times k \times (f + r + d) = 2,160$.

Note: 0 in the trend filter (x) indicates the investor take action immediately after a RA completes; the fixed holding days (f) are set as STW (1999); the stoploss rate (r) is set as HS in Chang and Osler (1999); the day filter (d) is set as STW (1999).

A.5 Double Top and Bottom (DTB)

There are two definitions of the DTB: first, the maximal closing prices of the first suberpiod and the third subperiod (M_1, M_3) are approximately even, and the minimal closing price of the second subperiod (m_2) is at least g percent lower than the average of M_1 and M_3. Second, the minimal closing prices of the first suberpiod and the third subperiod (m_1, m_3) are approximately even, and the maximal closing price of the second subperiod (M_2) is at least g percent higher than the average of m_1 and m_3. The term "approximately even" requires that the two tops in double-top pattern, or the two bottoms in the double-bottom pattern, are within a range of their average. In this study, we tried five ranges $(\pm 0.005, \pm 0.01, \pm 0.015, \pm 0.03, \pm 0.05)$. The middle bottom (top) of DTB needs to lie within a gap rate (g) of the average of tops (bottoms) for at least 1 month (LMW (2000)). In this study, we tried the range of gap in five values $(\pm 0.005, \pm 0.01, \pm 0.015, \pm 0.03, \pm 0.05)$. Similar to the definitions of TA and RA, 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 than that of adjacent bottom subperiod(s).

The parameters of DTB are set as follows:

n (local length) = 20, 40, 60 (in days) (3 values);
k (range of bound) = 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 (in days) (4 values);
r (stoploss rate) = 0.005, 0.0075, 0.01, 0.015 (4 values);
d (day filter) = 2, 3, 4, 5 (4 values).

The total number is $n \times k \times g \times x \times (f + r + d) = 2,160$.

Note: local length (n) is required at least 20-day (about 1 month) by LMW (2000); Edwards and Magee (1997, pp. 159–160) recommended the gap rate (g) to be 0.15-0.2; 0 in the trend filter (x) indicates the investor take action immediately after the DTB completes; Edwards and Magee (1997, p. 161) recommended the trend filter (x) to be 0.03; fixed holding days (f) are set as STW (1999); the stoploss rate (r) is set as HS in Chang and Osler (1999); the day filter (d) is set as STW (1999).

A.6 Broadening Top and Bottom (BTB)

There are two definitions of the BTB: first, the maximal closing prices of the first, third and fifth subperiods (M_1, M_3, M_5 as tops) satisfy $M_1 < M_3 < M_5$, and the minimal closing prices of the second and fourth subperiods (m_2, m_4 as bottoms) satisfy $m_2 > m_4$. Second, the minimal closing prices of the first, third and fifth subperiods (m_1, m_3, m_5 as bottoms) satisfy $m_1 > m_3 > m_5$, and the maximal closing prices of the second and fourth subperiods (M_2, M_4) satisfy $M_2 < M_4$. Similarly, 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 than that of adjacent bottom subperiod(s).

The parameters of BTB are set as follows:
n (local length) = 5, 10, 20, 50 (in days) (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 (in days) (4 values);
r (stoploss rate) = 0.005, 0.0075, 0.01, 0.015 (4 values);
d (day filter) = 2, 3, 4, 5 (4 values). The total number is $n \times x \times (f + r + d) = 720$.
Note: 0 in the trend filter (x) indicates the investor take action immediately after the completion of BTB; Edwards and Magee (1997, p. 175) recommended the trend filter (x) to be 0.03; the fixed holding days (f) are set as STW (1999); the stoploss rate (r) is set as HS in Chang and Osler (1999); the day filter (d) is set as STW (1999).

A.7 Learning Strategy (LS)

The parameters of LS are set as follows:
m (memory span) = 2, 5,10, 20, 40, 60, 125, 250 (in days) (8 values);
r (review span) = 1, 5, 10, 20, 40, 60, 125, 250 (in days) (8 values).

The total number is 13 (12 classes of simple rules and one based on all classes × 36 ($m-r$ combinations) × 3 (performance measures) = 1,404.
Note: the review span is required to be less or equal to memory span, so there are 36 $m - r$ combinations.

A.8 Vote Strategy (VS)

The parameters of VS are set as follows: m (memory span) = 1, 2, 5, 10, 20, 40, 60, 125, 250 (in days) (9 values);

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

The total number is 2 (ballot methods)× 12 (classes of simple rules) × 37 ($m-r$ combinations) = 888.

Note: review span requires to be less or equal to memory span, so there are 37 $m - r$ combinations.

A.9 Position Changeable Strategy (PC)

The parameters of PC are set as follows: m (memory span) = 1, 2, 5, 10, 20, 40, 60, 125, 250 (in days) (9 values);
r (review span) = 1, 5, 10, 20, 40, 60, 125, 250 (in days) (8 values). The total number is 2 (ballot methods) × 12 (classes of simple rules) × 37 ($m-r$ combinations) = 888.

Note: the review span requires to be less or equal to memory span, so there are 37 $m - r$ combinations.

Appendix B: Reality Check with Mean Returns and Sharpe Ratio

STW (1999) considered two performance criteria, the mean returns and Sharpe ratio, in testing the profitability of technical trading rules. In the mean returns measure, the hypothesis testing is to test whether there exists a technical trading rule that makes significantly positive returns. That implies following joint null hypothesis testing (STW, 1999, eq. 4):

$$\mathbf{H_0} : \max_{k=1,\ldots,l} \mathbf{E} f_k \leq 0,$$

where f_k ($k = 1, ..., l$) is the mean returns of the k-th rule. If the null hypothesis above is rejected, there exists at least one trading rule that can generate positive return. The daily index returns $f_{k,t+1}$ is computed as below ($k = 1, ..., l$) (STW, 1999, eq. 2):

$$f_{k,t+1} \;=\; \mathbf{ln}[\mathbf{1} + Y_{t+1}\mathbf{S_k}(X_t, \beta_k)] - \mathbf{ln}[\mathbf{1} + Y_{t+1}\mathbf{S_0}(X_t, \beta_0)].$$

On the right hand side, the first term is the (t+1)-day's return by k-th rule, and the second term is the (t+1)-day's return by the benchmark ($\mathbf{S_0}$=0 for the zero-return benchmark). And (STW, 1999, eq. 3)

$$X_t = \{\mathbf{X_{t-i}}\}_{i=0}^{R},$$

the $\mathbf{X_t}$ is original price series, the X_t is the sequence comprised by $\mathbf{X_t}$ from $i = 0, ..., R$ for generating technical signal, and $Y_{t+1} = (\mathbf{X_{t+1}} - \mathbf{X_t})/\mathbf{X_t}$ is the daily return. R is set equal to 253, the number of traded days in 1989, because that 1989's data is used in generating signals but not in computing returns. t ranges from 1 to T, and T is 3032, the total number of traded days from 1989 to 2000. It is noted that, when the benchmark is zero-return, $f_{k,t+1}$ is exact the log daily return. The $\mathbf{S_k}(\cdot), \mathbf{S_0}(\cdot)$ are the signal functions and convert X_t and system parameters β_k and β_0 into market positions as $\{1, 0, -1\}$.

The estimate of expectation value of mean returns is calculated as (STW, 1999, eq. 1):

$$\bar{f}_k = \frac{1}{n} \sum_{t=R}^{T} \hat{f}_{k,t},$$

where k is the k-th rule ($k = 1, ..., l$), n is the number of prediction periods indexed from R (=253) through T (=3032) (253 is the number so that $n = T - R + 1$ =2,780, as a 11-year performance). For each day t, each trading rule generates daily return $\hat{f}_{k,t}$, and $\bar{f}_k$ is the average daily return of k-th trading rule ($k = 1, ...l$).

In Sharpe ratio criterion, the hypothesis testing is to examine whether the rule can generate significant average excess return per unit of risk. That implies following joint null hypothesis testing (STW, 1999, eq. 7):

$$\mathbf{H_0} : \max_{k=1,...,l} \{g(\mathbf{E}(h_k))\} \leq \{g(\mathbf{E}(h_0))\},$$

where (STW, 1999, eq. 11)

$$g(\mathbf{E}(h_k)) = \frac{\mathbf{E}(h^{(1)}_{k,t+1}) - \mathbf{E}(h^{(3)}_{k,t+1})}{\sqrt{\mathbf{E}(h^{(2)}_{k,t+1}) - (\mathbf{E}(h^{(1)}_{k,t+1}))^2}},$$

where the three elements are (STW, 1999, eq. 8–10)

$$h^{(1)}_{k,t+1} = Y_{t+1} \mathbf{S_k}(X_t, \beta_k),$$

$$h^{(2)}_{k,t+1} = (Y_{t+1} \mathbf{S_k}(X_t, \beta_k))^2,$$

$$h^{(3)}_{k,t+1} = r^f_{t+1},$$

where the r^f_{t+1} is the daily risk-free interest rate at $t+1$ which is converted from Federal funds rate as STW (1999). The expectations of h_k and h_0 are computed by arithmetic means. The sample statistics $\bar{f}_k$ are formulated as (STW, 1999, eq. 12)

$$\bar{f}_k = g(\bar{h}_k) - g(\bar{h}_0),$$

where (STW, 1999, eq. 13)

$$\bar{h}_k = \frac{1}{n}\sum_{t=R}^{T}\hat{h}_{k,t+1}, \quad k = 1, ..., l.$$

In bootstrapping, the resampling distribution is formed by B bootstrapping resampled values of $\bar{f}_k$, denoted as $\bar{f}^*_{k,i}$, where (STW, 1999, eq. 14–15)

$$\bar{f}^*_{k,i} = g(\bar{h}^*_{k,i}) - g(\bar{h}^*_{0,i}), \quad i = 1, ..., B,$$

$$\bar{h}^*_{k,i} = \frac{1}{n}\sum_{t=R}^{T}\hat{h}^*_{k,t+1,i}, \quad i = 1, ..., B.$$

Following STW (1999), we can use a risk-free interest rate benchmark based in Sharpe ratio criterion to conduct Reality Check.

Appendix C: Stationary Bootstrapping

STW (1999 and 2002) and White (2000) used the stationary bootstrap proposed by Politis and Romano (1994) to resample the time-dependent return series for each trading rules. Since there are l trading rules considered simultaneously, we have a return matrix $(T \times l)$ with component $X_{t,k}$ (logarithmic return), where t means the time (1 to T) and k indicates the k-th trading rule (1 to l). Then we have to generate B resampled return matrices, while each resampled return matrix $(T \times l)$ with component $X^*_{t,k}$ is generated as follows: first, a randomly-selected row $X_{t,1}, ..., X_{t,l}$ (t $\in$ { 1,..., T }) of the original return matrix is set to be the first resampled row $X^*_{1,1}, ..., X^*_{1,l}$. Then, with probability q, the second resampled row, $X^*_{2,1}, ..., X^*_{2,l}$, is random selected from the return matrix; with probability 1-q, the second resampled row is set to be the sequential row of previous resampled row $X_{t,1}, ..., X_{t,l}$, denoted as the $X_{t+1,1}, ..., X_{t+1,l}$. It is noted that the first row $X_{1,1}, ..., X_{1,l}$ is regarded as the sequential row of the last row $X_{T,1}, ..., X_{T,l}$ in resampling, and this process is known as "wrap-up" resampling. Above procedure is repeated till N resampled rows are collected to form a resampled return matrix. Continuing such a procedure, B resampled return matrices can be simulated to compute White's Reality Check. STW tried the q as 0.01, 0.1, and 0.5, but found the outcomes are similar. It is noted that, in the return matrix, each column $X_{1,k}, ..., X_{T,k}$ is the logarithmic return series of a specific technical rule, which is assumed to be strictly stationary and weakly dependent.

Allen, F. and R. Karjalainen. "Using Genetic Algorithms to Find Technical Trading Rules." *Journal of Financial Economics*, 51 (1999), 245–271.

Bass, T. A. *The Predictors.* New York, NY: Henry Holt and Company (1999).

Bauer, R. J., and J. R. Dahlquist. *Technical Market Indicators.* New York, NY: John Wiley and Sons (1999).

Bessembinder, H., and K. Chan. "Market Efficiency and the Returns to Technical Analysis." *Financial Management*, 27 (1998), 5–17.

Blume, L.; D. Easley; and M. O'Hara. "Market Statistics and Technical Analysis: The Role of Volume." *Journal of Finance*, 49 (1994), 153–181.

Brock, W.; J. Lakonishok; and B. LeBaron. "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns." *Journal of Finance*, 47 (1992), 1731–1764.

Brown, S. J.; W. N. Goetzmann; and A. Kumar. "The Dow Theory: William Peter Hamilton's Track Record Reconsidered." *Journal of Finance*, 53 (1998), 1311–1333.

Chan, L. K. C., and J. Lakonishok. "Institutional Trades and Intraday Stock Price Behavior." *Journal of Financial Economics*, 33 (1993), 173–199.

Chan, K.; A. Hameed; and W. Tong. "Profitability of Momentum Strategies in the International Equity Markets." *Journal of Financial and Quantitative Analysis*, 35 (2000), 153–172.

Chan, L. K. C.; N. Jegadeesh; and J. Lakonishok. "Momentum Strategies." *Journal of Finance*, 51 (1996), 1681–1713.

Chan, L. K. C.; J. Karceski; and J. Lakonishok. "The Risk and Return from Factors." *Journal of Financial and Quantitative Analysis*, 33 (1998), 159–188. Chan, L. K. C.; N. Jegadeesh; and J. Lakonishok. "The Profitability of Momentum Strategies." *Financial Analysts Journal*, 55 (1999), 80–90.

Chang, P. H. K., and C. L. Osler. "Methodological Madness: Technical Analysis and the Irrationality of Exchange-Rate Forecasts." *Economic Journal*, 109 (1999), 636–661.

Dissanaike, G. "Long-Term Stock Reversals in the UK: Evidence from Regression Tests." *British Accounting Review*, 31 (1999), 373-385.

DeMark, T. R. *The New Science of Technical Analysis.* New York, NY: John Wiley and Sons (1994).

Edwards, R., and J. Magee. *Technical Analysis of Stock Trends*, 7th ed. New York, NY: John Magee Inc (1997).

Fama, E. F., and M. E. Blume. "Filter Rules and Stock-Market Trading." *Journal of Business*, 39 (1966), 226–241.

Fernandez-Rodriguez, F.; C. Gonzalez-Martel; and S. Sosvilla-Rivero. "On the Profitability of Technical Trading Rules Based on Artificial Neural Networks: Evidence from the Madrid Stock Market." *Economics Letters*, 69 (2000), 89–94.

Gencay, R. "Non-Linear Prediction of Security Returns with Moving Average Rules." *Journal of Forecasting*, 15 (1996), 165–174.

Gencay, R. "The Predictability of Security Returns with Simple Technical Trading Rules." *Journal of Empirical Finance*, 5 (1998), 347–359.

Gencay, R. "Linear, Non-Linear and Essential Foreign Exchange Rate Prediction with Simple Technical Trading Rules." *Journal of International Economics*, 47 (1999), 91–107.

Jegadeesh, N. "Evidence of Predictable Behavior of Security Returns." *Journal of Finance*, 45 (1990), 881–898.

Jensen, M. C., and Benington, G. A. "Random Walks and Technical Theories: Some Additional Evidence." *Journal of Finance*, 25 (1970), 469-482.

Jones, C. M., and M. L. Lipson. "Sixteenths: Direct Evidence on Institutional Execution Costs." *Journal of Financial Economics*, 59 (2001), 253–278.

Jones, C. M. "A Century of Stock Market Liquidity and Trading Costs." Working Papers, Columbia University (2002).

Knez, P., and M. Ready. "Estimating the Profits from Trading Strategies." *Review of Financial Studies*, 9 (1996 Winter), 1121–1164.

Lakonishok, J., and S. Smidt. "Are Seasonal Anomalies Real? A Ninety-Year Perspective." *Review of Financial Studies,* 1 (1988), 403–425.

Lakonishok, J.; A. Shleifer; and R. W. Vishny. "Contrarian Investment, Extrapolation, and Risk." *Journal of Finance*, 49 (1994), 1541–1578.

LeBaron, B. "Persistence of the Dow Jones Index on Rising Volume." Working Papers, Department of Economics, University of Wisconsin - Madison (1991).

LeBaron, B. "Do Moving Average Trading Rule Results Imply Nonlinearities in Foreign Exchange Markets?" Working Papers, Department of Economics, University of Wisconsin - Madison (1992).

LeBaron, D., and R. Vaitilingam. *The Ultimate Investor*. Dover, NH: Capstone Publishing (1999).

Lehmann, B. N. "Fads, Martingales and Market Efficiency." *Quarterly Journal of Economics*, 105 (1990), 1–28.

Levich, R. M., and L. R. Thomas. "The Significance of Technical Trading-Rule Profits in the Foreign Exchange Market: A Bootstrap Approach." *Journal of International Money and Finance*, 12 (1993), 451–474.

Lewis, M. *Liar's Poker*, New York, NY: Penguin Group (1989).

Lo, A. W., and A. C. MacKinlay. "Data-Snooping Biases in Tests of Financial Asset Pricing Models." *Review of Financial Studies*, 3 (1990), 431–467.

Lo, A. W.; H. Mamaysky; and J. Wang. "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation." *Journal of Finance*, 55 (2000), 1705–1765.

Merton, R. C. "On the Current State of the Stock Market Rationality Hypothesis." in R. Dornbusch; S. Fischer; and J. Bossons ed. *Macroeconomics and Finance: Essays in Honor of Franco Modigliani*. Cambridge, MA: MIT Press (1987).

Neely, C. J.; P. Weller; and R. Dittmar. "Is Technical Analysis in the Foreign Exchange Market Profitable? A Genetic Programming Approach." *Journal of Financial and Quantitative Analysis*, 32 (1997), 405–426.

Neely, C. J. "Technical Analysis and the Profitability of U.S. Intervention." *Review of Federal Reserve Bank in St. Louis*, 80 (1998), 3–17.

Neely, C. J., and P. Weller. "Technical Trading Rules in the European Monetary System." *Journal of International Money and Finance*, 18 (1999), 429–458.

Neftci, S. N. "Naive Trading Rules in Financial Markets and Wiener-Kolmogorov Prediction Theory: A Study of 'Technical Analysis'." *Journal of Business*, 64 (1991), 549–571.

Politis, D. N., and J. P. Romano. "The Stationary Bootstrap." *Journal of the American Statistical Association*, 89 (1994), 1303–1313.

Pring, M. J. *Technical Analysis Explained*, Third Ed., New York, NY: McGraw-Hill (1991).

Pring, M. J. *Martin Pring on Market Momentum.* New York, NY: McGraw-Hill (1993).

Ready, M. J. "Profits from Technical Trading Rules." *Financial Management"*, 31 (2002), 43–61.

Rouwenhorst, K. G. "International Momentum Strategies." *Journal of Finance*, 53 (1998), 267–284.

Rouwenhorst, K. G. "Local Return Factors and Turnover in Emerging Stock Markets." *Journal of Finance*, 54 (1999), 1439–1464.

Shiller, R. J. *Irrational Exuberance.* Princeton, NJ: Princeton University Press (2000).

Siegel, J. J. *Stocks for the Long Run*, Third Ed., New York, NY: McGraw-Hill (2002).

Sullivan, R.; A. Timmermann; and H. White. "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap." *Journal of Finance*, 54 (1999), 1647–1691.

Sullivan, R.; A. Timmermann; and H. White. "Dangers of Data-Driven Inference: The Case of Calendar Effects in Stock Returns." *Journal of Econometrics*, 105 (2001), 249–286.

Sullivan, R.; A. Timmermann; and H. White. "Scientific Progress with Data Sharing." *Journal of Forecasting*, (2002), forthcoming.

Sweeney, R. J. "Beating the Foreign Exchange Market." *Journal of Finance*, 41 (1986), 163–182.

Sweeney, R. J. "Some New Filter Rule Tests: Methods and Results." *Journal of Financial and Quantitative Analysis*, 23 (1988), 285–300.

Taylor, M. P., and H. Allen. "The Use of Technical Analysis in the Foreign Exchange Market." *Journal of International Money and Finance*, 11 (1992), 304–314.

White, H. "A Reality Check for Data Snooping." *Econometrica*, 68 (2000), 1097-1126.

Table 1: Our Expanded Set of Technical Analysis.

	Pattern Class	Number
	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
	Head and Shoulders (HS)	1,200
Simple Trading Rules	Momentum Strategy in Price (MSP)	1,760
	Momentum Strategy in Volume (MSV)	1,760
	Triangle (TA)	720
	Rectangle (RA)	2,160
	Double Top and Bottom (DTB)	2,160
	Broadening Top and Bottom (BTB)	720
	Subtotal	**18,326**
Contrarian Trading Rules	**Subtotal**	**18,326**
	Learning Strategies (LS)	1,404
Investor's Strategies	Vote Strategies (VS)	888
	Position Changeable Strategies (PC)	888
	Subtotal	**3,180**
Total		**39,832**

Table 2: Mean Returns of the Best Rules (Strategies) in 1990–2000.

Sample	Best Rule (Strategy)	Mean Returns	p-Value
DJIA	MSV, 250-day oscillator by 5-day MA, 20% overbought/oversold rate, 50 fixed holding days.	14.67%	0.39
S&P 500	Contrarian OBV, 10-5 day cross MA.	15.38%	0.22
NASDAQ Composite	2-day MA with 0.001 multiplicative band.	38.19%	0.00^{**}
Russell 2000	2-day simple MA.	47.10%	0.00^{**}

Table 2 describes the annual mean returns of the best rules (strategies) from the proposed set of technical analysis and the results of White's Reality Check (White's p-value). In this table, p-value is computed by $q = 0.1$ under Reality Check, nevertheless similar results are found in $q = 0.01$ and 0.5. The symbol ($**$) signifies significance at 1% level. It is noted that White's Reality Check is conducted on daily base.

Table 3: Sharpe Ratio of the Best Rules (Strategies) in 1990–2000.

Sample	Best Rule (Strategy)	Sharpe Ratio	p-Value
DJIA	PC in OBV, 250-day memory span and 125-day review span, three-choice ballot.	1.31	0.27
S&P 500	PC in OBV, 250-memory span and 250-day review span, two-choice ballot.	1.19	0.36
NASDAQ Composite	2-day MA with 0.001 multiplicative band.	1.96	0.00**
Russell 2000	2-day MA with 0.001 multiplicative band.	2.72	0.00**

Table 3 describes the annual Sharpe Ratio of the best rules (strategies) from the proposed set of technical analysis and the results of White's Reality Check (White's p-value). In this table, p-value is computed by $q = 0.1$ under Reality Check, nevertheless similar results are found in $q = 0.01$ and 0.5. The symbol ($**$) signifies significance at 1% level. It is noted that White's Reality Check is conducted on daily base.

Table 4: Summary of Significantly Profitable Rules and Strategies in 1990–2000.

	NASDAQ Composite			Russell 2000		
class	Simple Rules	Contrarian Rules	Investor's Strategies	Simple Rules	Contrarian Rules	Investor's Strategies
FR	2	-	2	22	-	50
MA	2	-	14	13	-	50
SR	-	-	-	-	-	7
CB	-	-	-	-	-	5
OBV	2	-	2	-	-	-
MSP	-	-	-	-	-	7
MSV	-	-	7	-	-	-
HS	-	-	-	-	-	-
TA	-	-	-	-	-	-
RA	-	-	-	-	-	-
DTB	-	-	-	-	-	-
BTB	-	-	-	-	-	-
LS on all classes*			2			42
Total	6	0	27	35	0	161

Table 4 summarizes the significantly profitable rules and strategies under 1% significance level. The symbol "-" means that there exists no significantly profitable rule (or strategy) in that class. The term "LS on all classes" indicates the learning strategies based on all 12 simple trading rule classes, so the number within the cell shows how many LS based on all 12 classes are significantly profitable.

Table 5: Comparison Between the Best Technical Rules and Buy-And-Hold Policy.

	NASDAQ Composite			Russell 2000		
Annual Return	Best Rule	Best Rule with Covering Transaction Costs	Buy-And-Hold Policy	Best Rule	Best Rule with Covering Transaction Costs	Buy-And-Hold Policy
11-year average	38.2%	27.9%	21.5%	47.1%	37.2%	11.4%
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%
2001	27.9%	18.1%	-21.7%	21.4%	11.7%	-0.0%
2002	-22.3%	-32.4%	-41.2%	-34.4%	-44.0%	-21.7%

Table 5 lists the annualized log returns of the best rules in NASDAQ composite and Russell 2000 in 1990-2002, and the annual index returns of buy-and-hold policy during this period. In NASDAQ composite, we use the 2-day MA with 0.001 multiplicative band as the best rule from in-sample period 1990–2000. In Russell 2000, we use the 2-day simple MA as the best rule from in-sample period 1990–2000. Transaction cost is set to be 0.05% for each one-way transaction.