TRADING PROFITABILITY OF TECHNICAL STRATEGIES IN INDIVIDUAL STOCKS

RYUICHI YAMAMOTO

Department of International Business,
National Chengchi University,
64 sec. 2, Chih-nan Rd., Taipei, 116, Taiwan

This paper investigates the technical rules' profitability in 15 individual stocks listed in NYSE. By using 5-minute returns from 6 months sample from October to December in 2001 and from April to June in 2002, White's (2000) Reality Check bootstrap procedure is applied to 3,807 technical rules for correcting the data-snooping problem. The results show that none of the 15 stocks gives profitable trading strategies, implying that the profitable chances tend to disappear within 5 minutes.

1. Introduction

This paper examines the profitability and its statistical significance of intraday technical trading across 15 individual stocks listed in the New York Stock Exchange (NYSE). The NYSE Trades and Quotes (TAQ) dataset from October to December in 2001 and from April to June in 2002 is used with 5 minutes intervals, and 3,807 technical trading rules from filter, moving average, trading range break, and channel breakouts are examined. White's (2000) Reality Check bootstrap procedure is applied to the large sets of technical rules, in order to find the profitability and correct the data-snooping problem, which might occur when we find profitable rules due to pure luck.

There has been much academic work on technical trading strategies, but the conclusions on whether the technical trading is profitable are still mixed. Some of the previous literature shows that the technical rules are not successful for predicting return dynamics in more recent periods. For example, Sullivan, Timmermann, and White (1999) find that the technical rules are profitable in their dataset of the Dow Jones Industrial Average only before the stock market crash in 1987, but the profitability disappears during the periods of 1987-1996. Qi and Wu (2006) show that technical rules are still significantly profitable in 7 currency pairs of the foreign exchange markets.

However, most of those papers have focused on daily data, so those results would investigate the profitable opportunities from technical strategies when investors trade at daily trading horizons. Osler (2003) demonstrates that order clustering in the order book can explain two popular predictions from technical trading analyses (trends tend to be reversed around the round numbers while those tend to be intensified once the rate penetrates the round numbers). Her result implies the presence of predictable variations in return series in ultra high-frequency data.

There have been quite few papers analyzing trading profits from technical indicators by using tick-by-tick data. Motivated by that, this paper utilizes high frequency data with 5 minutes intervals to test the profitability of technical strategies. Marshall et al (2008) also uses the 5 minutes intervals of the transactions data for the Standard and Poor's Depository Receipts (SPDRs). However, they show that none of their 7,846 rules are able to beat the market even after the data snooping problem is corrected, although some profitability maybe expected there because 5 minutes data gives rules more opportunities to transact. Rather than the SPDRs profitability, this paper analyzes the profitability for individual stocks to ask whether traders could be able to make profits if they focus on trading a few stocks so frequently.

In addition to showing the profitability of individual stocks, this paper provides possible explanations on the results of Marshall et al (2008), i.e., why the SPDRs returns may not be profitable. One possible answer is that if some of the stocks would produce successful trading rules while some others would not, we would conclude that the technical rules in the composite returns are not profitable because the profitability for each stock is just averaged out. However, this paper shows that those are not profitable because none of the stocks produces successful trading rules after correcting the data-snooping biases.

Section 2 introduces the TAQ dataset and the average of summary statistics for the 15 stocks. Section 3 describes the White’s Reality Check bootstrap procedure and technical trading rules, which are used in this paper. Section 4 conducts empirical tests and the last section concludes.

2. Data and Summary Statistics

I examine transaction data on 15 stocks taken from NYSE TAQ (Trade and Quote), which covers six months from October to December in 2001 and from April to June in 2002. There are 129 trading days in total (64 trading days in the 2001 sample and 65 days in the 2002). I chose the 15 stocks from the larger size group in the S&P500 listed companies at that time.[1] The two different periods are chosen to investigate the performance of the technical rules in bull and bear markets. The NYSE composite index in Datastream is increased by 8.4% from October to December in 2001 while it is decreased by 11.6% from April to June in 2002.

The 5-minute returns are calculated by using the transaction prices recorded from 9:30am (the official start of trading on the NYSE) to 4pm (the official close of trading). I define the returns over the 5-minute interval as:

$$r_{t+1} = \frac{P_{t+1} - P_t}{P_t} \tag{1}$$

where P_t is the original transaction price series.

Table 1 gives the average summary statistics of the return series for all 15 stocks in the two sub-sample periods. The averages of the sample over 15 stocks are 4,690.5 in the three months in 2001 and 4,777.4 in the 2002 sample. The mean returns are mostly positive in the 2001 sample, while those are negative for most of the stock in the 2002 sample. Those reflect that the economy was in the bull in the 2001 and in the bear for the 2002 sample as shown in the NYSE composite index. These returns are strongly leptokurtic for the entire series and both sub-sample periods so that the averages of kurtosis are both more than 50. Most of the distributions look skewed to the left (11 stocks in the 2001 sample and 10 stocks in the 2002 show negative skewness), although the average for the first sub-sample shows positive. The statistics on kurtosis and skewness imply non-normal distributions for the individual stocks. Serial correlations are generally small and mostly negative for all series.

Table 1: Descriptive Statistics of Returns

	N	Meanx1000	Std.x1000	Skewness	Kurtosis
Oct.-Dec. 2001	***4690.5***	***0.017***	***2.268***	***0.112***	***50.794***
April -June 2002	***4777.4***	***-0.029***	***2.35***	***-1.874***	***106.346***

3. The White's Reality Check and Technical Trading rules

As shown in Table 1, the returns do not follow normal distribution. This result suggests that the t-test cannot be applied for testing profitability of technical trading rules. So, as Brock, Lakonishok, and LeBaron (1992) argued, the

[1] 15 stocks include American International Group, AT&T, Bristol Myers Squib, Coca Cola, DuPont, Exxon, General Electric, General Motors, Hewlett Packard, International Business Machines, Johnson & Johnson, Merck, Pfizer, Procter and Gamble, and Wal-Mart.

profitability should be evaluated by the bootstrap methodology. This paper uses the White's Reality Check bootstrap for dealing with the non-normal ultra high-frequency data as well as accounting for the potential data snooping biases.

White (2000) presents the test procedure on whether a given model has predictive superiority over a benchmark model after accounting data snooping effects. The White's (2000) Reality Check can be applied for testing the profitability of the best trading rule. It tests the null hypothesis that the profit generated by the best trading rule does not exceed that of a benchmark strategy. It gives an estimate of the true and nominal p-values for the null by bootstrapping simulations. The true p-value is the statistic, which is adjusted for data snooping by taking into account the entire universe of rules where the best rule is selected. So, this p-value indicates the significance of the profitability of the best rule in the universe of the whole trading rules. The nominal p-value is the significance simulated with the sample only in the best trading rule. So, this value ignores the effect of the data snooping. Therefore, the difference between the true and nominal p-values represents the magnitude of the data-snooping biases.

Applying the White's Reality Check procedure to the Dow Jones Industrial Average and S&P 500 datasets, Sullivan, Timmerman, and White (1999) provide empirical evidence on the profitability of the best trading rule among a wide set of trading rules. I follow their set-up for testing the profitability. The performance statistic for each trading rule is given by:

(2) $$\bar{f}_k = T^{-1}\sum_{t=1}^{T} f_{k,t+1} \quad \text{k=1,….,M}$$

where M is the number of technical trading rules, and T is the number of trading periods. $f_{k,t+1}$ is the performance measure observed at t+1. In my application, M is equal to 3,807. The performance measure $f_{k,t+1}$ is defined as:

(3) $$f_{k,t+1} = \ln\left[1 + r_{t+1}S_k\left(P_t, \beta_k\right)\right] - \ln\left[1 + r_{t+1}S_0\left(P_t, \beta_0\right)\right]$$

where P_t is the original price series. $S_k(\bullet)$ and $S_0(\bullet)$ are signal functions that map the price information into trading signals, which take 1 which represents a long position, -1 which represents a short position, and 0 which represents a neutral position. So, the performance measure, $f_{k,t+1}$, is the excess returns of a trading rule, k, from a benchmark return. The benchmark returns is the returns from long position for all periods.

I test the null hypothesis that the returns from the best technical trading rule are no better than those from the benchmark strategy. In other words,

$$H_0 : \max_{k=1,\dots,l} \{\bar{f}_k\} \leq 0$$

The rejection of the null gives us an implication that the best trading rule produces higher performance than the benchmark strategy.

In White (2000), the null hypothesis can be evaluated by applying the stationary bootstrap of Politis and Romano (1994) to the observed value of $f_{k,t+1}$. I will derive the Reality Check p-value to test that the best rule has superior performance than the benchmark. First, for each trading rule, I resample $f_{k,t+1}$ with replacement B times, and denote the resampled series as $f^*_{k,t+1,b}$ (b=1,….,B). Second, I calculate the average of the bootstrap returns as:

$$\bar{f}^*_{k,b} = T^{-1} \sum_{t=1}^{T} f^*_{k,t,b} \qquad \text{b=1,….,B}$$

I set B=500. Then I construct the following statistics:

$$\bar{V}_m = \max_{k=1,\dots,M} \left[\sqrt{T}\, \bar{f}_k\right]$$

$$\bar{V}^*_{M,b} = \max_{k=1,\dots,M} \left[\sqrt{T}\left(\bar{f}^*_{k,b} - \bar{f}_k\right)\right] \qquad \text{b=1,….,B}$$

The White's Reality Check p-value is obtained by comparing $\bar{V}_m$ and $\bar{V}^*_{M,b}$. In particular, I sort out $\bar{V}^*_{M,b}$ (b=1,…,B) and denote it as:

$\bar{V}^*_{S,(1)}, \bar{V}^*_{S,(2)}, \dots\dots, \bar{V}^*_{S,(B)}$.

I then find N such that $\bar{V}^*_{S,(N)} \leq \bar{V}_m < \bar{V}^*_{S,(N+1)}$. The White's Reality Check p-value is given as:

$$p - value = 1 - N/M$$

I choose the smoothing parameter equal to 0.1.

The White's Reality Check evaluates the performance of the best trading rule among the wide set of the trading rules. This paper considers the following four types of trading rules, which are often used in previous academic papers on technical trading: filter rules, moving averages, trading range break, and channel breakouts. I follow the definitions by Sullivan et al. (1999).[2] Total number of the rules considered in this paper is 3,807.

---

[2] The parameter values are given as follows. *x*=0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.25, 0.3, 0.4, and 0.5. *y*=0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.04, 0.05, 0.075, 0.1, 0.15, and 0.2. *e*=1, 2, 3, 4, 5, 10, 15, and 20. *c*=5, 10, 25, and 50. Assuming that *y* is less than *x*, there are 497 filter rules. The parameter values for moving average rules are given as follows. *n*=2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, and 250. *m*=105, which is the number of fast-slow

4. Empirical Results

Table 2 summarizes the average performances of the best rule in the 15 stocks. The average numbers of trades are 482.6 in the 2001 sample and 474.8 in the 2002 sample from about 4,700 samples in total in both sub-periods. Mean returns of the best trading rule are all positive but quite small, which are 0.00008 in the 2001 sample and 0.000088 in the 2002 sample. The nominal p-values are close to zero for all stocks in the 2002 sample, but a bit higher on average in the 2001 sample. However, the most striking result is that almost all of the White's p-values are 1. Even for the stocks which do not show the White's p-value equal to 1, the values are quite close to 1. These results imply that there are severe data-snooping biases in the performance of the best trading rules. Once I account for the effect of the data-snooping, all of the best trading rules are not profitable anymore. These results imply that the stock traders cannot make profits by using technical trading strategies even if they trade individual stocks so frequently like every 5 minutes.

Table 2: Average Performance of the best trading rule

	# of trades	Mean return x 1000	Nominal p-value	White's p-value
Oct.-Dec. 2001	***482.6***	***0.08***	***0.09***	***1***
April -June 2002	***474.8***	***0.088***	***0.03***	***0.9992***

Marshall et al. (2008) find that none of their 7,846 trading rules are profitable over 5-minute intervals in their composite index dataset once the data-snooping problem is corrected. The results in this paper would suggest that their results are totally based on the fact that stock traders cannot make any profit even if they focus on trading a few stocks. These results would be consistent with the recent improvements of the market transparency and transaction technology. In most of the stock markets like Tokyo Stock Exchanges, Paris Bourse, or London Stock Exchange, some of the order book information has been available to stock traders without large delay like the last transaction prices,

---

combinations of *n*. *b*=0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, and 0.05. *d*=2, 3, 4, and 5. Total number of moving average rules is 2,040. *tb*=5, 10, 15, 20, 25, 50, 100, 150, 200, and 250. Total number of trading range break rules is 520. *tb* is the number of the previous periods to calculate the maximum or minimum for the trading range breaks. *cb*=5, 10, 15, 20, 25, 50, 100, 150, 200, and 250. *xb*=0.005, 0.01, 0.02, 0.03, 0.05, 0.075, 0.1, and 0.15. Total number of channel breakouts is 750. A channel is produced when the high over the previous *cb* periods is within *xb* percent of the low over the previous *cb* periods.

orders around the best prices, and so on. This gives traders more chances to find any profitable opportunities so soon. Actually, since the transactions are immediately conducted through computer systems, the profitable opportunities tend to disappear so quickly. My results imply that as a result of such improvements the profitable chances would disappear within 5 minutes.

5. Conclusion

This paper analyzes and interprets the profitability of 3,807 technical trading strategies for 15 stocks of the larger size firms in NYSE. White's Reality Check bootstrapping procedure is applied to the 5-minute returns series to correct the data-snooping problem. The results say that once I consider the effect of the data-snooping, all 15 stocks do not produce any significant profitable chance to any technical trading rules. Since the trading frequency is 5-minutes here, this implies that stock traders may have to trade so frequently to make profits. In addition, my result would suggest that technical rules are not profitable in trading composite index because those rules are not profitable even in trading individual stocks.

References

1. Brock, W., J. Lakonishok, and B. LeBaron (1992): "Simple technical trading rules and the stochastic properties of stock returns" *Journal of Finance* 37, 1731-1764.
2. Marshall B., R. Cahan, and J. Cahan (2008): "Does intraday technical analysis in the US equity market have value?" *Journal of Empirical Finance* 15, 199-210.
4. Osler, C. (2003) "Currency orders and exchange rate dynamics: An Explanation for the Predictive Success of Technical Analysis" *Journal of Finance* 58, 1791-1820.
5. Politis, D., and J. Romano (1994): "The stationary bootstrap" *Journal of the American Statistical Association* 89, 1303-1313.
6. Qi, M and Y. Wu (2006) "Technical trading-rule profitability, data snooping, and reality check: evidence from the foreign exchange market" *Journal of Money, Credit, and Banking*, 38, 2136-2158.
7. Sullivan, R., A. Timmermann, and H. White (1999) "Data-snooping, technical trading rule performance, and the bootstrap" *Journal of Finance* 54, 1647-1691.
8. White, Halbert (2000): "A Reality Check for Data Snooping." *Econometrica* 68, 1097-1126.