“Technical trading strategies with market impact”

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Technical trading strategies with market impact

Abstract

The paper proposes an empirical estimation of the market impact on the profitability of technical trading strategies for institutional investors. A benchmark for the performance of large trades among institutional investors, volume weighted average price (VWAP) is used as a proxy for the execution price of large trades. By comparing to the performance using the closing price as the execution price, the authors investigate a representative set of technical rules, including the moving average and trading range break-out rules, using the NYSE/AMEX securities with the NYSE TAQ data set from 1993 to 2005. Empirical results show that the market impact is estimated to be a spread of 1.4% per annum. The authors also find that technical trading strategies are not profitable after considering market impact.

Keywords: volume weighted average price, market impact, technical trading strategies.
JEL Classification: G10, G20.

Introduction

It is common that institutional investors implement trading strategies for their portfolios. While institutional investors adopt different classes of trading strategies subject to their investment objectives, they typically evaluate and select optimal ones through back-testing using historical data. The most frequently used data is the closing price. However, the assumption that institutional investors can always execute their large orders at the closing price without price impact can be violated. In this study, we hypothesize that failing to execute trading strategies at closing price can result in a significant profit reduction.

Technical analysis is a discipline of security analysis to forecast the future price trend by using historical financial data − mainly price and volume. Many empirical studies, including Fama and Blume (1966), Jensen and Bennington (1970), Knez and Ready (1996), Allen and Karjalainen (1999), Marshall et al. (2008), conclude that technical analysis is not useful for improving returns. Despite its many criticisms, technical analysis has been popular among investors and financial analysts. Brock et al. (1992) show the forecasting ability of 26 technical trading rules on the Dow Jones Industrial Average (DJIA) over a period of 90 years. Furthermore, some other empirical studies, including Sweeney (1988), Allen and Taylor (1990, 1992), Neely et al. (1997), Gencay (1998), Sullivan et al. (1999), Lo et al. (2000), show the usefulness of technical trading rules. Blume et al. (1994), Friesen et al. (2009) also advocate using theoretical models that technical analysis can be valuable. Park and Irwin (2007) summarize main recent findings regarding the profitability of technical trading strategies. Recently, Shynkevich (2012) shows that after adjusting for data snooping bias, technical trading strategies can not outperform buy-and-hold strategies. Menkhoff (2010) finds that technical trading strategies are common in Germany, Switzerland, the United States, Italy and Thailand.

All previous studies in the literature, however, assume implicitly that trades can be executed at the daily closing price. We take a different approach and test the hypothesis of whether the performances of technical trading strategies are affected by market impact. In technical analysis, a majority of traders base their investment plan on the closing price of securities. The closing price represents the final evaluation of the stock made by the market on a given trading day, which is readily available and well-published. Hence, traders often track errors relative to the close of stocks. This post-trade benchmark promotes trading at the closing price, through market orders being placed towards the end of the day or guaranteed market-on-close orders. Trading at the closing price involves hidden costs which can be significant. Cushing and Madhavan (2000) show that there are greater market impacts if trading at the close because prices are more sensitive to order flows at this point. Even ordinary retail investors can hardly execute their trade at around the close without market impacts. Chan and Lakonishok (1995) use a special data set of 37 large investment firms to illustrate the market impact of their trades. Therefore, we conclude that it is generally difficult for institutional investors to execute all their trades at the closing price as their trades are usually of large volume.

The transaction costs institutional investors bear are not just explicit such as broker commissions and taxes but also implicit ones. Compared with explicit transaction costs, implicit transaction costs for institutional investors can be much higher. One significant implicit cost to institutional investors is the market impact, which is caused by unfavorable price movements due to the execution of large trades.

To avoid market impact, large trades are not executed at once. Instead, the order is typically split up for execution over the day to participate proportionately in the day's volume. When institutional investors divide their trade into separate orders, the first order can affect the price of subsequent trades. Such market impact costs can be substantial. Although many researchers, including Dufour and Engle (2000) and Lee and Ready (1991), attempt to measure the price impact of a trade, there is still no accurate method to estimate implicit costs before the trade.

The volume weighted average price (VWAP) is a popular benchmark for measuring the performance of traders and computing trading costs. Revealed by a survey conducted by the Bank of America (2007), VWAP execution orders represent around 50% of all the trading activities by institutional investors. The popularity of using VWAP as a benchmark is mainly because of its computational simplicity. Although the computation of VWAP may involve data-intensive calculations, it is provided by a number of vendors such as Reuters and Bloomberg. In addition, VWAP is better than any fixed time benchmarks as it improves both market transparency and efficiency (Cushing and Madhavan, 2000). Ting (2006) also shows empirically that VWAP is closer to the efficient price compared with the closing price.

Market impact can be measured by comparing the execution price of a large order with the VWAP benchmark (Berkowitz et al., 1988). As a result, institutional investors implement VWAP strategies (Madhavan, 2000; Bialkowski et al., 2008) to reduce implicit transaction costs. A VWAP strategy involves buying or selling a fixed number of shares tracking VWAP at an average price. There are some examples of VWAP strategies:

1. Direct access: orders are traded by investors themselves, either through participation strategies or market timing strategies to beat VWAP.
2. Agency trading: orders are given to broker-dealers to trade on an agency basis to track VWAP.
3. Automated participation strategies: orders are split up over the day to participate proportionately in the day's volume, trading as intelligently as possible and with minimal market impact.

Manual trading is labor-intensive and costly. For a large equity trade, in order to get the average execution price as close to VWAP as possible to avoid price movement risk, the orders are typically placed in automated participation strategies, which lower the explicit costs and minimize price impact by spreading the liquidity demand of large orders across the trading period.

Both the closing price and the VWAP are potentially informative and convenient reference prices. However, since institutional investors cannot generally execute large orders at the closing price, it is unreasonable to evaluate their trading strategies based on the closing price. Theoretically, the execution could be completed as if it was traded by any randomly selected trader implementing VWAP strategies which could outperform or underperform the VWAP benchmark. We argue that on average they can execute large orders at the daily VWAP. Therefore, compared with the closing price, VWAP should be a more realistic proxy to evaluate trading strategies for institutional investors.

Under the assumption that institutional investors execute orders at VWAP, it also creates an impetus to compare the closing price with VWAP in generating trading strategies through an empirical study of any trading strategy using historical price as input. Accordingly, we test the following hypotheses:

H1: Evaluating technical trading strategies using VWAP produces lower returns than using closing price.

H2: For institutional investors who execute orders at VWAP, using of VWAP to generate technical trading strategies produces higher returns than using closing price.

If H1 is true, it supports the intuition that market impact affects the profitability of trading strategies. To test the two hypotheses, we follow the framework of Brock et al. (1992) who test 26 technical trading rules under moving averages and trading range breaks on the daily price of DJIA over the period from 1897 to 1986. They find that buy signals consistently generate higher returns than sell signals, and provide evidence for the predictive power of the 26 technical rules. The findings has raised the interest of many researchers to investigate whether similar results hold for other major stock markets using similar research methods, such as the London Stock Exchange FT30 index for the period from 1935 to 1994 (Mills, 1997), the Financial Times Industrial Ordinary Index in the UK for the period from 1935 to 1994 (Hudson et al., 1996), 6 stock market indices in Asia, namely Japan, Hong Kong, Korea, Malaysia, Thailand, and Taiwan over the period from 1975 to 1991 (Bessembinder and Chan, 1995), and the Chilean equity market index over the period of 1987 to 1998 (Parisi and Vasquez, 2000). All of them conclude that the trading rules are quite successful in producing a return greater than a buy-and-hold strategy in their respective sample periods.

We focus on those technical rules studied in Brock et al. (1992), namely the moving average rules and the trading range break rules, to test our hypotheses empirically. The moving average rules are especially chosen as they are widely used. Allen and Taylor (1992) survey dealers in the London Foreign Exchange and find that over 90% of the respondents use some forms of technical analysis to predict returns. The moving average rules are among the most popular trading rules being used. Early investigations of the moving average rules by Van Home and Parker (1967) and James (1968) show that none of them were successful when compared with a buy-and-hold strategy. However, some recent researches support the use of moving average rules. El-Khodary (2004) points out that moving average rules are the most profitable technical trading rules which help traders gauge trend directions. They reckon that "moving averages are excellent indicators to confirm existing trends in spite of their lag".

The main idea behind the moving average rule is to average a number of past reference prices. The calculated average represents the price area nearest to a proportionately large number of trades in that time period. Such area is where the fewest people have extreme gains or losses for the period. Therefore, the pressure to trade out of fear or greed tends to be diminished. Averaging can smooth the fluctuation in the prices so that the underlying trends can be signaled out.

According to El-Khodary (2009), all types of moving average rules do not predict market movements lagging the current price. In a bull market, the moving average is below the rising price line and vice versa for a bear market. This is the idea behind variable length moving average rule. When the price changes its direction, the moving average line crosses the price line. Hence, depending on the direction of the crossing, buy or sell signals can be identified. This is known as the fixed length moving average rule. However, the simplest form of moving average rules is criticized for its equal weighting in averaging the reference prices in the specified period, assuming that old prices are equally relevant to more recent ones.

Conrad and Kaul (1998) suggest that momentum strategy, including the moving average rule, is useful and usually profitable at the medium horizon (3 to 12 months), while Lesmond et al. (2004) find that stocks generating large momentum returns are precisely those with high trading cost and conclude that the magnitude of abnormal returns from trading strategies does not imply a profit opportunity. Thus, it is interesting to investigate the momentum strategies, particularly the variable-length moving average rule, fixed-length moving average rule and trading range breakout rule using different execution price such as VWAP.

This empirical study examines the results of applying technical trading rules, including ten variable-length moving average rules, ten fixed-length moving average rules and six trading range break rules, to the stocks in New York Stock Exchange (NYSE) and American Stock Exchange (AMEX), over a 13-year period from January 1993 to December 2005, with closing price and VWAP acting either as trading strategy generator, or execution price, or both. Existing similar studies include Kavajecz and Odders-White (2004) who test the liquidity effect of technical analysis using limit order book data. The main contributions to existing literature are, first, to find out the profitability of technical analysis to institutional investors with market impact as opposed to ordinary retail investors, and second, to compare whether closing price or VWAP is more favorable as trading strategy generator for institutional investors with market impact.

1. Data and technical rules

1.1. Data. The data used in this study include all securities listed on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) from the Center for Research in Security Prices (CRSP) in Wharton Research Data Services (WRDS). Only common stocks listed on NYSE are included. This is done by excluding all the stocks in the CRSP database with share code (SHRCD) other than 10 or 11, and excluding those with exchange code (EXCHCD) other than 1.

The intraday transaction data, including the price and volume traded for the same securities, is also retrieved from WRDS but through another dataset Trade and Quote (TAQ). Since WRDS started providing TAQ data from 1993, we collect data from January 1993 to December 2005. We clean the records in TAQ according to the standards in the literature (see for example Liu and Maheu, 2008). Invalid trades are filtered out by using correction indicator. The trade data is kept only if the correction indicators equal 0 or 1, which refer to regular trade and later-corrected trades respectively. The daily VWAP is calculated based on the intraday transaction data with the formula:

$$VWAP = \frac{\sum_{i=1}^{N} Trasaction\ \ Price_i \times Volume_i}{Daily\ \ Share\ \ Volume}.$$

Since the closing price and VWAP are obtained from two different datasets, inconsistency is unavoidable. We include a particular stock in our study only if both its closing price and VWAP records are available for the same period of time.

Since small-cap stocks are usually not considered by institutional investors, we exclude stocks with low market capitalization. In order not to exasperate the survivorship bias, we sort all the stocks with trading data over the period from January 1993 to December 2005 by their market capitalizations of their first trading days throughout this period. We impose a 80th percentile of market capitalization rule on all the stocks as the criterion for stock selection, which is roughly equivalent to considering stocks with market capitalization greater than 2 billion US dollars. As a result, all stocks with market capitalization on their first trading day greater than 2 billion US dollars are included in our studies. This stock filtering criterion is better than the one which just sorts the stocks according to the market capitalization of one single trading day, in that we would not exclude stocks with large market capitalization but not being traded on the chosen trading day. The number of stocks satisfying all the above criteria is 458.

1.2. Technical trading rules. We evaluate the same set of twenty-six technical trading rules following Brock et al. (1992), including ten Variable Length Moving Average (VMA) rules, ten Fixed Length Moving Average (FMA) rules and six Trading Range Break (TRB) rules, with the closing price and VWAP acting as signal generators and execution prices. The assumption behind the rules is that, upon a buy signal, an investor is to borrow and double the investment in the stock; upon a sell signal, an investor is to sell shares and use the proceed to invest in a risk-free asset.

The moving average rule varies with the length of time periods (short/long term), inclusion of band, type of MA models (variable-length moving average/fixed-length moving average), and type of price data (closing price/VWAP). The length of time periods involves two moving averages of stock price level, namely short-term moving average of order n and long-term moving average of order m ($m > n$). A trend is being identified if the relative positions of short-term and long-term moving averages can be located. Generally speaking, when the short-term moving average penetrates the long-term moving average, buy and sell signals are generated. The rule can be varied by the length of time periods. Following Brock et al. (1992) to use the most popular rules, we investigate the 1-50 (short period is 1 day and long period is 50 days), 1-150, 5-150, 1-200 and 2-200 MA rules.

Banding can eliminate false buy or sell signals, i.e. signals that result in losses, when the short and long term moving averages are close to each other. Brock et al. (1992) also introduce a one percent band so that a signal is generated only when the short-term moving average is above or below the long-term moving average by one percent. In this paper, the MA rules with and without the one percent band are tested.

The VMA rules generate a buy (sell) signal when the short-term moving average is above (below) the long-term moving average. This rule simulates a strategy that traders go long as the short-term moving average moves above the long-term moving average and go short vice versa. For a zero band, all days are classified as either buy or sell. For a one percent band, signals are generated only if the short-term moving average is above (below) the long-term moving average by an amount larger than the band.

The FMA rules generate a buy (sell) signal when the short-term moving average cuts the long-term moving average from below (above). The holding period is 10 days as suggested by Brock et al. (1992)[1]. Returns are recorded at the end of each holding period. In addition, signals occurring during this 10-day period are ignored. As the signal can only be based on historic data, a one-day lag is unavoidable.

The TRB rules generate a buy (sell) signal when the price penetrates the resistance (support) level, which is defined as a local maximum (minimum) over m trading days. The idea behind TRB rules is that many investors are willing to buy at around the minimum price, thus making it difficult for the price to further penetrate its support level. In case the price drops and penetrates the support level, it is expected to further drift downwards. The rationale is vice versa for that of the resistance level. Therefore, technical analysts recommend buying when the price rises above the last peak and selling when the price sinks below its last trough.

Following Brock et al. (1992), the number of days being tested (m) are 50, 150 and 200. The rule is also tested with and without a one percent band to eliminate false signals. Similar to the FMA rules, returns are calculated after 10 trading days and any signal during the 10-day holding period is ignored.

2. Empirical results

In the first hypothesis, we test the significance of difference between the returns evaluated by closing price and VWAP respectively. Since the signals are generated from the same set of closing prices, the most suitable test statistic for this is the t-test for paired samples.

[1] According to Brock et al. (1992), the selection of 10-day returns is arbitrary. For some rules they tried two-week return and obtained essentially the same results.

The t-statistic is

$$\frac{\mu_D}{\sqrt{\sigma_D^2 / N}},$$

where μ_D and σ_D^2 are the mean and variance of the return differences respectively, and N is the number of signals.

In the second hypothesis, the signals generated from the closing price and VWAP can differ. Therefore, we use the Welch t-test (Welch, 1938) where the t-statistic for the differences is

$$\frac{\mu_v - \mu_c}{\sqrt{\frac{\sigma_v^2}{N_v} + \frac{\sigma_c^2}{N_v}}},$$

where μ_c and μ_v are the means of the excess returns over the unconditional mean return using the closing price and VWAP as the input respectively, σ_c^2 and σ_v^2 are the variances of the excess returns using the closing price and VWAP as the input respectively, and N_c and N_v are the numbers of signals generated by the closing price and VWAP respectively. The degree of freedom associated with this t-distribution

$$\frac{\left(\frac{\sigma_v^2}{N_v} + \frac{\sigma_c^2}{N_c}\right)}{\frac{\left(\frac{\sigma_v^2}{N_v}\right)^2}{N_v - 1} + \frac{\left(\frac{\sigma_c^2}{N_c}\right)^2}{N_c - 1}}.$$

To test the two hypotheses, we take a different approach compared to Brock et al. (1992) when we compute the difference of the combined returns between buy and sell strategies. The buy-sell returns here aggregate the returns from the buy signal and the negative returns from the sell signal. Each trading rule is applied to individual eligible stocks and each return generated from the trading rule is used as a sample return.

2.1. Is evaluating trading strategies using VWAP less profitable? For the institutional investors with market impact, we are interested in whether executing orders with VWAP differs significantly compared with closing price. Table 1, Table 2 and Table 3 (see Appendix) examine the differences with VMA, FMA, and TRB rules respectively.

Table 1 shows that all the differences of buy returns are positive. Under six out of ten sets of parameters, we reject the null hypothesis that evaluating buying strategies with VWAP is at least as profitable as with closing price at 5 percent significance. For the differences of sell returns, the results also support the hypothesis. Similar results can be obtained from the tests for overall return. Table 2 shows results even more supportive to the hypothesis. All differences of buy returns are positive and we reject the null hypothesis at 5 percent significance level for each set of parameters. Similar conclusions are drawn for sell returns and overall returns. Table 3 shows the results for TRB. We reject the null hypothesis at 5 percent significance level in all sets of parameters for buy, sell, and overall returns.

The empirical results for the three popular trading rules in technical analysis support the hypothesis that evaluating trading strategies using VWAP is less profitable than using the closing price. Giving equal weights on each of the 26 trading rules, the average estimated market impact is 1.379% per annum.

2.2. Is using VWAP to generate trading strategies more profitable than using closing price for institutional investors? The results presented in the last section suggest that there is a statistically significant difference between evaluating trading strategies using VWAP and closing price. In this section, we ask a further question as to whether generating signals using VWAP is more profitable compared with using closing price for institutional investors, i.e., we assume that we evaluate all trading strategies using VWAP. Table 4, Table 5, and Table 6 show the results for the VMA, FMA, and TRB rules respectively.

In Table 4 (see Appendix), the results for the trading strategies generating signals with the closing price are presented in column 2, 4, 6, 8, 10 with the number of buy signals, the number of sell signals, mean of the returns from buy signals, mean of the returns from sell signals, and mean of the overall returns from the VMA rules. Similarly, the results for the trading strategies generating signals with VWAP are presented in column 3, 5, 7, 9, 11. The average of the difference is about 0.0026 percent, or 0.95 percent per annum. However, most of the tests results are only significant at 20 percent level and only one of them is significant at 10 percent level. We fail to reject the null hypothesis that the returns of generating signals with VWAP is better than those with the closing price at 10 percent significance level using a one-tailed test. For sell returns, the results are similar. Only one of the ten tests can reject the null hypothesis at 10 percent significance level. For the overall returns presented in column 10 and 11, all excess returns from signal generator VWAP is around 0 while those from the closing price is negative. The average of these difference is 0.0031 percentage, which is 0.7812 percent per annum. While it can be seen that using VWAP to generate trading strategies can improve performance, the results are not significant.

Table 5 shows the results for FMA. Generating signals with VWAP produces a higher return than generating with the closing price. The average of the differences for overall returns is about 0.0624, which is an 1.5725 percent per annum. However, results are not statistically significant. Table 6 shows the results for TRB. Generating signals with VWAP produces a higher return than generating with closing price. The average of the differences in overall returns is about 1.5095 percent. However, none of the ten one-tailed tests is significant for buy, sell, and overall returns.

While the empirical tests for the second hypothesis is not conclusive compared with the first hypothesis, they partially support that using VWAP as an input for generating trading strategies can improve the performance for institutional investors. One explanation for the difference being less significant is that closing price actually contains similar if not the same information as VWAP and therefore using VWAP to generate trading strategies may not improve the performance significantly.

The empirical results also show that even if VWAP is used as the signal generator, the technical trading rules are not profitable after considering market impact during the period from 1993 to 2005. While most of the studies in the literature tend to support the usefulness of technical analysis, their studies mainly focus on market indices while in this paper we focus on a large class of individual stocks together with market impact. As a result, we conclude that market impact does affect the profitability of technical trading strategies.

Conclusion

By using VWAP as a proxy for evaluating technical trading strategies under market impact, we empirically show that the effect of market impact on the profitability is significant. Empirical results show that evaluating technical trading strategies using VWAP is less profitable compared with using closing price. A possible reason is that institutional investors need to compensate for the implicit trading costs resulted from large trades. The reduction in returns could also be due to the mismatch between the technical trading strategy generator and the execution price. We then further test on whether using VWAP to generate trading strategies improves the performance of those technical rules. The empirical results generally support this hypothesis but with less statistical significance. This could partially be explained by the fact that closing price and VWAP contain roughly the same market information. Therefore, using VWAP to generate trading strategies may not improve the performance substantially. Finally, empirical results also show that the technical trading strategies are not profitable if VWAP is the execution price. The data set covers a period of time with various condition of market volatility and therefore the results are valid for a range of market volatility condition. Future research may include testing more technical trading strategies to further investigate the profitability under market impact.

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Appendix

Table 1. Difference between executing with VWAP and closing for VMA rules

Test	*N*(*Buy*)	*N*(*Sell*)	*Buy*	*Sell*	*Buy-Sell*
(1, 50, 0)	574699	438949	0.0049 (3.1856)	-0.0064 (-2.8767)	0.0056 (4.2703)
(1, 50, 0.01)	508795	376339	0.0057 (3.4066)	-0.0077 (-3.0603)	0.0065 (4.5524)
(1, 150, 0)	582802	385379	0.0038 (2.5047)	-0.0058 (-2.3304)	0.0046 (3.4100)
(1, 150, 0.01)	548173	352134	0.0040 (2.5485)	-0.0054 (-2.0183)	0.0045 (3.2082)

Table 1 (cont.). Difference between executing with VWAP and closing for VMA rules

Test	*N*(*Buy*)	*N*(*Sell*)	*Buy*	*Sell*	*Buy-Sell*
(5, 150, 0)	583505	384674	0.0011 (0.7402)	-0.0018 (-0.7271)	0.0014 (1.0364)
(5, 150, 0.01)	547719	350824	0.0010 (0.6627)	-0.0010 (-0.3626)	0.0010 (0.7158)
(1, 200, 0)	578316	367072	0.0027 (1.7907)	-0.0040 (-1.5658)	0.0032 (2.3647)
(1, 200, 0.01)	549876	339784	0.0030 (1.9580)	-0.0047 (-1.7263)	0.0037 (2.5957)
(2, 200, 0)	578487	366910	0.0017 (1.1627)	-0.0026 (-0.9954)	0.0021 (1.5202)
(2, 200, 0.01)	549839	339580	0.0020 (1.2630)	-0.0026 (-0.9604)	0.0022 (1.5621)
Average			0.0030	-0.0042	0.0035

Notes: The sample period is from January 1993 to December 2005. "Test" is the VMA trading rule specified as the number of days to calculate the long-term moving average, the number of days to calculate the short term moving average, the band as a percentage of the short-term moving average. "*N*(*Buy*)" and "*N*(*Sell*)" are the numbers of buy and sell signals in the sample. "*Buy*" and "*Sell*" are the mean returns generated from VMA rules with executing at the closing price less executing at the VWAP by buy signals and sell signals respectively. The *t*-ratios below in the parentheses test the null hypothesis that executing at VWAP generates at least the same return as executing at the closing price against executing at VWAP generates lower buy (higher sell) return than executing at the closing price. "*Buy-Sell*" are the overall returns generated from VMA rules with the closing price as the execution price less those with the VWAP as the execution price. The *t*-ratios below are from the one-tailed test for the null hypothesis that executing at VWAP generates at least the same overall return smaller as executing at the closing price. All returns are reported in percentage level.

Table 2. Difference between executing with VWAP and closing for FMA rules

Test	*N*(*Buy*)	*N*(*Sell*)	*Buy*	*Sell*	*Buy-Sell*
(1, 50, 0)	14384	15823	0.0215 (2.0018)	-0.0832 (-7.7634)	0.0538 (7.0851)
(1, 50, 0.01)	12169	13035	0.0623 (5.2440)	-0.0968 (-7.9466)	0.0801 (9.4062)
(1, 150, 0)	7787	8617	0.0693 (4.9639)	-0.0901 (-6.0630)	0.0802 (7.8346)
(1, 150, 0.01)	6483	6998	0.0552 (3.5435)	-0.1017 (-5.7655)	0.0793 (6.7057)
(5, 150, 0)	6142	6532	0.0607 (3.9547)	-0.0546 (-3.3259)	0.0576 (5.1086)
(5, 150, 0.01)	5218	5446	0.0284 (1.7252)	-0.0275 (-1.4926)	0.0279 (2.2562)
(1, 200, 0)	6527	7235	0.0516 (3.3930)	-0.1174 (-7.0330)	0.0862 (7.5859)
(1, 200, 0.01)	5424	5900	0.0415 (2.3971)	-0.1286 (-6.5656)	0.0869 (6.6029)
(2, 200, 0)	5975	6486	0.0362 (2.3300)	-0.0919 (-5.2214)	0.0652 (5.5195)
(2, 200, 0.01)	5007	5323	0.0470 (2.7196)	-0.0885 (-4.3852)	0.0684 (5.1210)
Average			0.0474	-0.0880	0.0686

Notes: The sample period is from January 1993 to December 2005. "Test" is the FMA trading rule specified as the number of days to calculate the long-term moving average, the number of days to calculate the short-term moving average, the band as a percentage of the short-term moving average. "*N*(*Buy*)" and "*N*(*Sell*)" are the numbers of buy and sell signals in the sample. "*Buy*" and "*Sell*" are the mean returns generated from FMA rules with executing at closing price less executing at the VWAP by buy signals and sell signals respectively. The *t*-ratios below in the parentheses test the null hypothesis that executing at VWAP generates the same return as executing at the closing price against executing at VWAP generates lower buy (higher sell) return than executing at the closing price. "*Buy-Sell*" are the overall returns generated from FMA rules with the closing price as the execution price less those with the VWAP as the execution price. The *t*-ratios below are from the one-tailed test for a null hypothesis that executing at VWAP generates at least the same overall return as executing at the closing price. All returns are reported in percentage level.

Table 3. Difference between executing with VWAP and closing for TRB rules

Test	*N*(*Buy*)	*N*(*Sell*)	*Buy*	*Sell*	*Buy-Sell*
(1, 50, 0)	24184	16256	0.0525 (6.9343)	-0.0802 (-6.1770)	0.0636 (9.2097)
(1, 50, 0.01)	17725	12649	0.0674 (7.2342)	-0.0848 (-5.2379)	0.0746 (8.6187)

Table 3 (cont.). Difference between executing with VWAP and closing for TRB rules

Test	*N*(*Buy*)	*N*(*Sell*)	*Buy*	*Sell*	*Buy-Sell*
(1, 150, 0)	15292	7039	0.0509 (5.6878)	-0.0640 (-2.7290)	0.0551 (5.7316)
(1, 150, 0.01)	11002	5627	0.0661 (5.9274)	-0.0732 (-2.5385)	0.0685 (5.5994)
(1, 200, 0)	13563	5572	0.0514 (5.4383)	-0.0776 (-2.8489)	0.0590 (5.6859)
(1, 200, 0.01)	9724	4497	0.0725 (6.1684)	-0.0864 (-2.6084)	0.0769 (5.8247)
Average			0.0601	-0.0777	0.0663

Notes: The sample period is from January 1993 to December 2005. "Test" is the TRB trading rule specified as the number of days to calculate the long-term moving average, the number of days to calculate the short-term moving average, the band as a percentage of the short-term moving average. "*N*(*Buy*)" and "*N*(*Sell*)" are the numbers of buy and sell signals in the sample. "*Buy*" and "*Sell*" are the mean returns generated from TRB rules with executing at closing price less executing at the VWAP by buy signals and sell signals respectively. The *t*-ratios below in the parentheses test the null hypothesis that executing at VWAP generates the at least same return as executing at the closing price against executing at VWAP generates lower buy (higher sell) return than executing at the closing price. "*Buy-Sell*" are the overall returns generated from TRB rules with the closing price as the execution price less those with the VWAP as the execution price. The *t*-ratios below are from the one-tailed test for the null hypothesis that executing at VWAP generates at least the same overall return as executing at the closing price. All returns are reported in percentage level.

Table 4. Difference between generating with VWAP and closing for VMA rules

Test	*N*(*Buy*)	*N*(*Buy*)*	*N*(*Sell*)	*N*(*Sell*)*	*Buy*	*Buy**	*Sell*	*Sell**	*Buy-Sell*	*Buy-Sell**
(1, 50, 0)	574699	575209	538949	438596	-0.0170	-0.0136	0.0203	0.0158	-0.0184	-0.0145
					(1.0821)		(-0.9323)		(1.4122)	
(1, 50, 0.01)	508795	509562	376339	375919	-0.0203	-0.0153	0.0244	0.0175	-0.0220	-0.0162
					(1.4729)		(-1.2820)		(1.9304)	
(1, 150, 0)	582802	583462	385379	384743	-0.0146	-0.0116	0.0218	0.0172	-0.0175	-0.0138
					(1.0100)		(-0.8429)		(1.2978)	
(1, 150, 0.01)	548173	548486	352134	351603	-0.0157	-0.0125	0.0224	0.0182	-0.0183	-0.0147
					(1.0212)		(-0.7366)		(1.2222)	
(5, 150, 0)	583505	583804	384674	384401	-0.0098	-0.0080	0.0146	0.0119	-0.0117	-0.0095
					(0.6000)		(-0.5068)		(0.7755)	
(5, 150, 0.01)	547719	548031	350824	350570	-0.0098	-0.0083	0.0148	0.0136	-0.0117	-0.0104
					(0.4596)		(-0.2167)		(0.4632)	
(1, 200, 0)	578316	578727	367072	366678	-0.0136	-0.0115	0.0221	0.0189	-0.0169	-0.0144
					(0.6911)		(-0.5808)		(0.8916)	
(1, 200, 0.01)	549876	550248	339784	339410	-0.0143	-0.0119	0.0244	0.0196	-0.0182	-0.0148
					(0.8028)		(-0.8148)		(1.1419)	
(2, 200, 0)	578487	578738	366910	366667	-0.0123	-0.0104	0.0201	0.0172	-0.0153	-0.0130
					(0.6281)		(-0.5312)		(0.8126)	
(2, 200, 0.01)	549839	550198	339580	339211	-0.0128	-0.0111	0.0200	0.0177	-0.0156	-0.0136
					(0.5483)		(-0.3899)		(0.6531)	
Average					0.0026		-0.0037		0.0031	

Notes: The sample period is from January 1993 to December 2005. Those columns with (without) * are the results for VMA rules with VWAP (the closing price) as the signal generator. "*N*(*Buy*)" and "*N*(*Sell*)" are the numbers of buy and sell signals reported in the sample. All returns are reported in percentage level and in terms of excess return, i.e. daily return less the unconditional daily return of each stock. The *t*-ratios below in the parentheses test the null hypothesis that generating signals with the closing price produces at least the same returns as generating with the VWAP.

Table 5. Difference between generating with VWAP and closing for FMA rules

Test	*N*(*Buy*)	*N*(*Buy*)*	*N*(*Sell*)	*N*(*Sell*)*	*Buy*	*Buy**	*Sell*	*Sell**	*Buy-Sell*	*Buy-Sell**
(1, 50, 0)	14384	13873	15823	15164	0.0822	0.1139	0.0463	-0.0025	0.0163	0.0557
					(0.4127)		(0.6372)		(0.7481)	
(1, 50, 0.01)	12169	11760	13035	12550	0.0628	0.1424	0.0358	-0.0326	0.0118	0.0857
					(0.9411)		(-0.8353)		(1.2562)	
(1, 150, 0)	7787	7475	8617	8229	0.0152	-0.0343	0.1225	0.0514	-0.0571	-0.0433
					(-0.4848)		(-0.7095)		(0.1934)	
(1, 150, 0.01)	6483	6251	6998	6659	-0.0062	0.0118	0.1479	0.0188	-0.0797	-0.0040
					(0.1609)		(-1.1174)		(0.9416)	

Table 5 (cont.). Difference between generating with VWAP and closing for FMA rules

Test	*N*(*Buy*)	*N*(*Buy*)*	*N*(*Sell*)	*N*(*Sell*)*	*Buy*	*Buy**	*Sell*	*Sell**	*Buy-Sell*	*Buy-Sell**
(5, 150, 0)	6142	6075	6532	6450	0.1521	0.1866	0.0531	0.0048	0.0464	0.0880
					(0.3135)		(-0.4183)		(0.5217)	
(5, 150, 0.01)	5218	5177	5446	5406	0.1689	0.1927	0.0306	0.0071	0.0670	0.0906
					(0.2013)		(-0.1794)		(0.2671)	
(1, 200, 0)	6527	6266	7235	6872	-0.0964	-0.0097	0.2160	0.1661	-0.1593	-0.0915
					(0.7844)		(-0.4597)		(0.8746)	
(1, 200, 0.01)	5424	5235	5900	5651	-0.1759	-0.0539	0.2729	0.1557	-0.2264	-0.1067
					(1.0055)		(-0.9382)		(1.3719)	
(2, 200, 0)	5975	5842	6486	6338	-0.0666	-0.0262	0.1507	0.0549	-0.1104	-0.0411
					(0.3548)		(-0.8211)		(0.8479)	
(2, 200, 0.01)	5007	4912	5323	5242	-0.1670	-0.0645	0.1795	0.0832	-0.1734	-0.0742
					(0.8146)		(-0.7245)		(1.0826)	
Average					0.0490		-0.0746		0.0624	

Notes: The sample period is from January 1993 to December 2005. Those columns with (without) * are the results for FMA rules with VWAP (the closing price) as the signal generator. "*N*(*Buy*)" and "*N*(*Sell*)" are the numbers of buy and sell signals reported in the sample. All returns are reported in percentage level and in terms of excess return, i.e. daily return less the unconditional daily return of each stock. The *t*-ratios below in the parentheses test the null hypothesis that generating signals with VWAP produces better returns than generating with the closing price.

Table 6. Difference between generating with VWAP and closing for TRB rules

Test	*N*(*Buy*)	*N*(*Buy*)*	*N*(*Sell*)	*N*(*Sell*)*	*Buy*	*Buy**	*Sell*	*Sell**	*Buy-Sell*	*Buy-Sell**
(1, 50, 0)	24184	24184	24960	16256	-0.2454	-0.2034	0.4385	0.3239	-0.3230	-0.2518
					(0.8271)		(-1.2154)		(1.4655)	
(1, 50, 0.01)	17725	17725	17333	12649	-0.4406	-0.4429	0.5358	0.4217	-0.4802	-0.4340
					(0.0363)		(-0.9907)		(0.7603)	
(1, 150, 0)	15292	15292	15723	7039	-0.2108	-0.1626	0.4812	0.3303	-0.2961	-0.2158
					(0.8212)		(-0.8635)		(1.1748)	
(1, 150, 0.01)	11002	11002	10656	5627	-0.4345	-0.4096	0.5938	0.4787	-0.4884	-0.4333
					(0.3364)		(-0.5522)		(0.6383)	
(1, 200, 0)	13563	13563	13955	5572	-0.2053	-0.1392	0.4911	0.3702	-0.2885	-0.2070
					(1.0704)		(-0.5810)		(1.0879)	
(1, 200, 0.01)	9724	9724	9440	4497	-0.3889	-0.3721	0.5195	0.4749	-0.4302	-0.4050
					(0.2159)		(-0.1797)		(0.2643)	
Average					0.0326		-0.1103		0.0599	

Notes: The sample period is from January 1993 to December 2005. Those columns with (without) * are the results for TRB rules with VWAP (the closing price) as the signal generator. "*N*(*Buy*)" and "*N*(*Sell*)" are the numbers of buy and sell signals reported in the sample. All returns are reported in percentage level and in terms of excess return, i.e. daily return less the unconditional daily return of each stock. The *t*-ratios below in the parentheses test the null hypothesis that generating signals with VWAP produces better returns than generating with the closing price.