Size, Information Asymmetry and the Role of Technical Analysis

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Abstract

This paper examines the value of technical trading strategies across firms in five size quintile groups in the Stock Exchange of Thailand between 1998-2006. The construction of size quintiles is to proxy for different levels of information asymmetry. The Sharpe ratio and breakeven transaction costs are used to evaluate trading rules based on the Daily Moving Average (DMA) and the Moving Average Convergence Divergence (MACD) relative to the performance of a benchmark naïve Buy and Hold strategy. The paper finds empirical evidence that technical trading strategies are more successful when applied to small cap stocks suggesting that informational efficiency is not shared evenly across all market segments. The result is robust to tests of time varying returns using bootstrap methodology.

I Introduction

Equity markets become more efficient overtime. With improvement on the speed and accuracy of information disclosure by firms, investor also improve the speed of reaction which in turn becomes quickly reflected in security prices. However, the level of information efficiency might not be shared evenly across overall market.

Analysts' coverage tends to focus on large firms thus leaving smaller firms out. In addition, the level and precision of information reveal to public are more disclosed and likely to have higher quality on large firms. This suggest a special role for learning from price and volume, particularly in small stocks (See Blume, Easley, and O'Hara (1994))

This paper investigates the value of technical trading strategy in Thai market across different market capitalization, which proxies for the different level of information quality and information asymmetry. From all stocks listed in Stock Exchange of Thailand, we screen the stocks to assure that the only stock which has enough trading activities are included, the 5 size quintiles indices are constructed by equally-weight consists of 20 stocks in each quintile. To evaluate the trading rules, the Sharpe ratio is calculated to compare and evaluate performance of technical strategies. Breakeven transaction costs are also calculated to account for the nature that technical trading strategy is transaction-intensive. The performances of technical trading strategies are compared to a naïve buy & hold strategy.

The technical trading strategies chosen in this paper is the daily moving average (DMA) and the moving average convergence divergence. These two strategies are the most widely used in the financial industry. To examine the robustness of the trading across size quintiles, a bootstrap methodology is used in this study by imposing null models generated by GARCH (1, 1) and EGARCH (1, 1) with 2 conditional distributions Gaussian and student's t. The paper finds that only the technical trading rules imposed on smaller stocks can provide returns higher than our benchmark buy & hold strategy. When the rules are applied to large cap stocks, they not longer outperform the benchmark return.

II Existing literatures

Referring to an article by *Park and Irwin (2006)* published in journal of economic survey**,** which reviewed many of the technical trading rule studies. The earliest empirical study included in *Park and Irwin (2006)* review is in 1960, classified studies into 2 period, early studies and modern studies.

Early studies (1960-1988): In early studies, most of them investigate performance of several technical trading rules in stock market, foreign exchange market and future market. Included trading rules are filters, stop-loss orders, moving averages, momentum oscillators and relative strength. Majority of early technical trading studies are on foreign exchange markets and future markets, finds substantial net profits while there are mixed results in stock market. These results suggest that stock markets were more efficient than foreign exchange markets or future markets before the mid-1980s, yet those early studies have several limitations in testing procedures. For example First, early studies generally consider a small number of trading systems, typically only one or two trading systems. Second, most early studies do not conduct statistical tests of significance on technical trading systems. Last, several authors speculate that substantial technical trading profits find in early studies are attributable to data snooping biases. Since there are no structural form of a technical trading systems that pre-specifies parameters.

Modern studies (1988-2004): Modern studies are assumed to start since 1988. Including studies investigate performance of technical trading rules in capital market, future market and foreign exchange market. Although modern studies have improved upon the limitations of early studies in terms of testing procedures, there are still considerable differences with regard to treatment of transaction cost, risks, parameter optimization, out-of-sample tests, statistical tests and data snooping. In *Park and Irwin (2006)* review, modern studies are categorized into 7 groups on the basis of differences in testing procedures. Seven groups are consist of 'Standard', 'Model-based bootstrap', 'Reality check', 'Genetic programming' which attempts to quantify and solve for data snooping, 'Non-linear' such as feed forward neural network and 'Chart pattern'.

The reviewed literatures under bootstrap methodology which will be employed in this study are classified into 2 groups, first, studies of technical trading rules in developed market, second, studies of technical trading rules in emerging markets which includes Thailand.

Review literatures in developed market

The most influential study under bootstrap methodology is *Brock et al. (1992)* uses 90 years of daily Industrial Average of Dow Jones Index from 1986 to 1986 to examine predictive ability of moving average and trading range break. *Brock et al. (1992)* investigates trading rules performance under various non-overlapping sub-periods and finds support for predictive ability of technical trading strategies, however in *Brock et al. (1992)* do not account for impact of transaction cost and non-synchronous trading.

Hudson et al. (1996) adopt the technical trading rules studied in *Brock et al (1992)* and apply it in United Kingdom stock market which is costly trading environment. The results support predictive ability of technical trading rules, however it do not allow investors to make excess returns after adjusting for transaction cost of 1% per round trip.

Bessembinder and Chan (1998) further investigate technical trading rules predictive ability identified by *Brock et al (1992)*, extend *Brock et al (1992)* study by adjusting for impacts of related transaction costs and non-synchronous trading by using one day lagged price to calculate returns. Bessembinder and Chan (1998) results support *Brock et al. (1992)* findings. They conclude that trading rule predictive ability is not solely attributable to returns measurement error arising from non-synchronous trading. Their results suggest that buy signals generate positive return, whereas sell signals offer negative returns and have more significant predictive ability.

Le Baron (2000) use the same dataset as Brock et al. (1992) but include the later 10 years data from 1988 to 1999 (to avoid 1987 crash), The results suggest that returns following a buy signal are not significantly larger than the return following sell signal.

Kwon and Kish (2002) extend Brock et al. (1992) study by including trading volume moving averages on NYSE and NASDAQ covering both large-cap and small-cap firms using market weightings. They conduct Bootstrap methodology by utilizing random walk and GARCH-M analysis. The results suggest that technical trading rules provide values to investors, compare with benchmark buy-and-hold strategy. The results reveal a weakening in profit potential overtime. Imply that markets are becoming more efficient.

For the effects of non-synchronous trading, *Neely and Weller (2003)* suggest that technical analyses are widely used by practitioners for short horizon trading. They use daily opening and closing prices to calculate returns, if an open price trig a buy signal, closing price on the same day is used to calculate return. Using opening and closing prices to generate buy and sell signals and in calculating returns helps control for the non-synchronous trading problem.

Most of the reviewed literatures are mainly focus on stock indexes which consist of large stocks and ignored small stock. Therefore, they do not attempt to examine the performances of trading rules across firms of different sizes which is the main objective of this study. However, the following 2 reviewed literatures examine trading rules performances across firms of different sizes.

Marshall, Qian and Young (2005) examine returns to a selection of moving average rules apply to individual US stocks listed in the NYSE and NASDAQ market using Bootstrap methodology under period from 1990 to 2004 including 866 NYSE and 199 NASDAQ stocks. For the treatment of non-synchronous trading, *Marshall (2005)* examines the results in 2 approaches. First, buy/sell position take place on the signal date. Second, buy/sell position take place on the day following signal date. The result suggests that trading rules are more likely to provide significantly negative returns rather than positive returns. There are some evidences suggest that trading rules are more likely to generate significantly positive returns when apply to larger and more liquid stocks.

Chandrashekar (2005) study the performances of DMA strategy in NYSE, AMEX and NASDAQ stock markets by using the Bootstrap methodology. Extend the study to investigate the performances of DMA across firm of different sizes by study ten size deciles indexes. The paper hypothesize that technical trading rules have greater timing ability in small firms. Using firm sizes as a proxy for the differences in the level of information efficiency and information asymmetry across firm sizes. The finding suggests that trading rules are more appropriate in smaller stocks.

Reviewed literatures in emerging market and Thailand

There are some differences between the reviewed literatures in emerging market and this study. First, these reviewed literatures are mainly focus on the stock indexes which consist of large stocks and ignore small stocks. Second, none of them attempt to examine the performances of trading rules across firm sizes which is the main objective of this study.

Bessembinder and Chan (1995) investigate trading rules studied in Brock et al (1992) by using daily equity market indexes of six Asian countries (Hong Kong, Japan, Korea, Malaysia, Thailand and Taiwan) over the period 1975-1991. The results support the predictive ability of trading rules in emerging markets of Malaysia, Thailand and Taiwan. The finding suggests that trading rule profits are decreasing overtime in the more mature market like in Hong Kong and Japan.

Ratner and Leal (1999) examine the performances of ten Variable Moving Average (VMA in ten emerging equity markets in Latin America and Asia (Thailand is included) from 1982 to 1995. The average of differences in buy-sell returns after trading costs for each rule and country are compared to benchmark buy and hold strategy, their result indicates that Taiwan, Thailand and Mexico are markets where technical trading strategies may be profitable but there is no strong evidence for other markets. However they find that trading rule combinations test disregarding their statistical significance, correctly predict the direction of changes in the return series.

Marshall and Cahan (2005) test Variable Moving average rules in New Zealand stock market index which is known as small market, with short-selling constraints, lack of analyst coverage and loose insider trading regulation, its characteristics suggest that New Zealand capital market may be less efficient than overseas market like in developed market. This raises the possibility that trading rules might be profitable. Using bootstrap methodology with common null models they find that trading rules is not profitable similar to those in large offshore developed market.

Pichai-utkrit, Sakulwisit (2003) investigate performances of six trading rules Variable Moving Average, Fixed Moving Average, Trading Range Break, Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD) and Stochastic in Thailand in the period of 1987-2002 find that all six rules are profitable before transaction cost but only TRB still profitable after transaction cost. The statistical test is run by t-test not with the Bootstrap methodology. They examined the performance only on stock index which ignore small stocks.

Piyaissarakul, Ditkaew, Rattanapan (2004) investigate performances of TRB rules on individual stock in SET50 index, find that TRB rule is able to make excess returns in most of the stock but only 10 out of 30 still profitable after transaction cost. However, the statistical test is run by t-test not with the Bootstrap methodology.

Thaweepan, Thuesat, Chatborirak (2006). examine performances of trading rules in SET index, the data used are daily closing price from 1975 to 2005 , evaluate the performance of trading rules in overall period and 3 non-overlapping sub-periods. Trading rule returns are benchmark with naïve buy and hold strategy, statistical tests are examine with both t-test and bootstrap methodology under Random walk, AR(1) and GARCH-M. Their result reveals the weakening in trading rules potential profit overtime. However, in their study do not examine Bootstrap results under null EGARCH model which is widely used in reviewed paper in developed market.

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III Data description

The data used in this study is daily closing prices for all stocks in stock exchange of Thailand from period of January 1997 to December 2006 obtained from DATASTREAM. This full sample period consists of 10 years data. All the stocks are then screened by 2 rules, first, only the stock that listed from the beginning until the ending of study period are included, second, the stocks that has number of non-trade per year more than 20% are then filtered out to assure that only the stock that has enough trading activities are included. After apply the screening rules we have totally 100 stocks in our sample, all the screened stocks are then arrange into 5 size quintiles by market value, the member of each quintile are readjusted every year. Then we construct the equally-weight index of each size quintile to represent the price movement of various firm sizes.

Table I provides the summary statistic for all 5 size quintiles in the study period. The mean daily returns are positive in quintile 1 and 3, which is 0.0134% for smallest stock and 0.0103% for quintile 3. Where as mean daily returns are negative for quintile 2, 4 and 5. As summary statistics indicate, the daily returns distribution is not follows a normal distribution which is the evident from the summary statistic including skewness, kurtosis, and the Kolmogorov-Smirnov normality test statistic(D-stat).

Note that the standard deviations of return are very high, that is 36.5%, 42.75%, 36.9%, and 37.86% for quintile 1, 2, 3 and 4 respectively, and volatility is lowest in the biggest quintile which is at 20.82% per year.

[Insert Table I about here]

IV Framework
Technical trading rules strategies

Moving Average Convergence Divergence: is one of the popular technical trading rules used by technical analyst in financial industry. The standard formula for the MACD is the difference between a security's 26-day and 12-day exponential moving averages (MACD line is equals to EMA (fast) – EMA (slow)), the two moving averages that make up MACD, the 12-day EMA is the fast exponential moving average and the 26-day EMA is the slow EMA. Closing prices are used to form the moving averages. The 9-day EMA of MACD is plotted along side to act as a trigger line. MACD requires 3 parameters consists of fast, slow and signal as the numbers of days used to calculate the exponential moving average.

Exponential moving average calculation: for example the EMA of 3 days

Period	closing prices	previous EMA	EMA (3)	
1	2			
2	3			
3	4		3	
4	5	3	4	[0.5 * (5-3)] +3
5	5	4	4.5	[0.5 * (5-4)] +4
6	6	4.5	5.25	[0.5 * (6-4.5)] +4.5

Smoothing constant (K) = 2/ (1+days) in this example: 2/ (1+3) = 0.5

The first period EMA: this is only the simple moving average of n days (in this sample 3days), EMA period 3 = (2+3+4)/3 =3

EMA = K (closing price – previous EMA) + Previous EMA

MACD (12, 26, 9) is written as 12 days, 26 days and 9 days to calculate exponential moving average for fast, slow and signal line, respectively.

MACD buy signals are given when the bullish moving average crossover occur that is when MACD lime move from lower the signal line then rise above the signal line. The sell signal is just the mirror of buy signal that is when MACD lime moves from above the signal line then falls below the signal line.

Although, the choices of the days used to construct the exponential moving average in MACD are quite arbitrary and there might be no explanation, however this study use the standard formula of MACD and does not try to find the optimized trading rule.

DMA Daily moving average the moving average strategy is one of the simplest and most common used in the study of technical trading rules. It has been used for more than 70 years. The different lengths used in this study are 200, 150, 100, 50, 5, 2 and 1 days, where 200, 150, 100 and 50 are used as long period moving average, 5,2 and 1 day are used as the short period moving average. The buy signal is given when the short period moving average rises from below the long period moving average to above the long moving average, the sell signal is given when the short moving average falls from above the long moving average to below the long moving average. The 1% band is also introduced as the percentage differences required to generate signal.

In this study, in every trading rules test we adjust for the effect of non-synchronous trading, which means that, if the buy (sell) signal is emitted on day t the long (short) position will take place on the next day t+1. Adjust for the fact that the price series used in this study are closing prices, thus it is difficult for investors to take position on that particular signal date.

Measuring returns

In measuring the performance of technical trading rules, the naïve buy & hold strategy is use as a benchmark, which means that investors buy the stock or index at the beginning of the period and hold until the end of the period. This study assumes that investors are risk-averse and care about risk-adjusted returns rather than raw returns. Since different strategies could encounter different amount of risks and trading strategies could expect higher return simply because it is more risky and higher returns are just to compensate for higher risk. Thus this study uses ‘Sharpe ratio’ to evaluate performances among trading strategies and to account for the risk incorporate with the trading strategy.

Note that the annual return used to calculate Sharpe ratio is pre-trading cost. However, since technical trading strategy is transactions intensive, to evaluate the performance of trading strategy after transaction costs, the ‘Breakeven transaction cost’ are calculated. The breakeven transaction cost is the implied transaction cost that makes investors indifferent between using technical trading strategy and the benchmark buy & hold strategy.

$$\frac{r_{macd} - r_f - c}{\sigma_{macd}} = \frac{r_{buyhold} - r_f}{\sigma_{buyhold}}$$

The breakeven transaction cost approach is similar to the approach of *Chandrashekar (2005*). The implied transaction cost ‘c’ that equates the above equation will be divided by number of trade per year. In the case of no short-sale constraint, the implied transaction cost will be divided by average number of buy and sell per year to arrives the implied round-trip transaction cost, when short-sale constraint is imposed the implied transaction cost will be divided with the average number of buy transaction.

For all the technical trading rules tested, we calculate the average daily return, annualized returns, annualized sell returns and annualized buy & hold returns. Specifically, we define the average daily returns as the mean daily return for the MACD rule and the period which the rule is in the long (short) position.

$$\bar{r}_{macd} = \frac{1}{N_{macd}} \sum_{t=1}^{T} I_{macd}(t) r_t \qquad \bar{r}_{bh} = \frac{1}{N_{bh}} \sum_{t=1}^{T} r_t$$

$$\bar{r}_{b} = \frac{1}{N_{b}} \sum_{t=1}^{T} I_{b}(t) r_t \qquad \bar{r}_{s} = \frac{1}{N_{s}} \sum_{t=1}^{T} I_{s}(t) r_t$$

Where r_t represents the compounded return, $\bar{r}_{macd}$ is the mean daily return from MACD rule (long and short), $\bar{r}_b$ is the mean daily returns only from buy signal and $\bar{r}_s$ is the mean daily returns only from sell signal, $\bar{r}_{bh}$ is the mean daily return from the benchmark Buy & Hold strategy. The indicator variable I_{macd} take the value of 1 when buy signal is given, -1 when sell signal is given and zero otherwise, I_b is the indicator variable that take value of 1 when buy signal is given and zero otherwise, similar to indicator I_s that take value of 1 when given sell signal and zero otherwise, Thus if $\bar{r}_s$ takes negative value implies that MACD sell signal has ability to identify the negative return periods. The N_{macd} is the number of days under MACD when short-sale is allowed, N_b and N_s are the number of days where the rule is long or short, respectively.

The annualized returns are computed as:

$$\bar{r}_{macd,annual} = \frac{1}{N_p}\sum_{t=1}^{T} I_{macd}(t)\, r_t \qquad \bar{r}_{bh,annual} = \frac{1}{N_p}\sum_{t=1}^{T} r_t$$

$$\bar{r}_{b,annual} = \frac{1}{N_p}\sum_{t=1}^{T} I_{b}(t)\, r_t \qquad \bar{r}_{s,annual} = \frac{1}{N_p}\sum_{t=1}^{T} I_{s}(t)\, r_t$$

Where $\bar{r}_{macd,annual}$, $\bar{r}_{b,annual}$ and $\bar{r}_{s,annual}$ are the annualized MACD, buy and sell returns, respectively, $\bar{r}_{bh,annual}$ is the annualized buy & hold return. N_p represents number of year in the period which is 10 years in this study.

The average daily standard deviation of return can be computed by, first, finding the product between r_t and the indicator variable in each case to get the column vector of returns, then we can compute the standard deviation of return which is an average daily standard deviation. Annualized standard deviation can be computed by times the daily standard deviation with the square root of time, in this study we assumes 250 days in one year.

Bootstrap null models

For the choices of the Bootstrap null models, refers to study of Thaweepan, Thuesat, Chatborirak (2006) which study technical trading strategies on SET index in 3 non overlapping sub-periods. In their study they chose Random walk with drift, AR (1) and GARCH-M as null models.

They find that the null models Random walk with drift could not explain the movement of SET index in their last period from 1998-2005, which is much closed to our study period. In their paper they see the trend that SET index tends to move closer to the pattern of AR (1) and GARCH-M models, however in their study they do not perform the EGARCH as a null model, which was widely used as a null model by may studies in developing markets. Thus, in this study we choose EGARCH as a null model and we also uses GARCH (1, 1) to compare the results whether null model could more explain the movements of our constructed size quintile indexes.

Maximum log likelihood estimation is used to estimate models parameters, model specification for condition means and condition variances are described below.

GARCH (1, 1)

$$r_t = C + \phi r_{t-1} + \theta \varepsilon_{t-1} + \varepsilon_t \qquad \text{Condition mean equation}$$

$$\sigma_t^2 = K + G\sigma_{t-1}^2 + A\varepsilon_{t-1}^2 \qquad \text{Condition variance equation}$$

With constraints

$$\sum_{i=1}^{P} G_i + \sum_{j=1}^{Q} A_j < 1$$

$$K > 0$$

$$G_i \geq 0$$

$$A_j \geq 0$$

EGARCH (1, 1)

$$r_t = C + \phi r_{t-1} + \theta \varepsilon_{t-1} + \varepsilon_t \qquad \text{Condition mean equation}$$

$$\log \sigma_t^2 = K + G \log \sigma_{t-1}^2 + A\left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - E\left\{\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}\right\}\right] + L\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \qquad \text{Condition variance equation}$$

Where

$$E\left\{|z_{t-1}|\right\} = E\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}\right) = \begin{cases} \sqrt{2/\pi} & \text{Gaussian distribution} \\ \sqrt{\dfrac{\nu-2}{\pi}} \cdot \dfrac{\Gamma\left(\dfrac{\nu-1}{2}\right)}{\Gamma\left(\dfrac{\nu}{2}\right)} & \text{Student's t distribution} \end{cases}$$

With degree of freedom ν >2

For the estimation results for all return series are present in Table II

[Insert Table II about here]

V. Empirical results

MACD strategy across 5 quintiles

Results from the MACD trading strategy of all 5 size quintiles are presented in Table III. In Panel A is the results without short–sale constraint, that is investors can take short position when sell signal is emitted. Panel B is the result with short-sale constraint imposed. The first column contains all parameters in evaluating trading rule performances, which consist of 'trade per year' is the average number of trade per year, 'Daily return' and 'Annual return' is the corresponding MACD returns prior to transaction costs, 'Annual Sigma' is the volatility of returns, 'Annual sell return' is the corresponding size quintile's returns during sell signal period, 'Sharpe ratio' is the Sharpe ratio from technical trading strategy, 'break-even cost' is the percentage cost per trade that equates the sharp ratio between MACD and buy & hold strategy.

[Insert Table III about here]

Panel A, when short-sale is allowed, we can see the decreasing trend in the annual returns as firm size increases, in quintile 1 which consists of the 20 smallest stocks MACD strategy earns the annual return of 38.01%, in the size quintile 2 earns the annual return of 38.94% then sharply decreases to 26.02% in size quintile 3, 21.18% in quintile 4 and lowest at 10.07% per year in the quintile 5 which contains the 20 biggest firm size. Note that for all 5 quintile the annual MACD returns are higher than the benchmark buy & hold strategy.

We can see this trend clearer when considering the MACD Sharpe ratio in each size quintile which decreases monotonically as firm size increases, that is Sharpe ratio is highest at 0.9093 in the smallest quintile then decreases to 0.7993 in the second quintile, 0.5744, 0.4331 and 0.2449 in the quintile 3, 4 and 5 respectively. Note that the volatility of returns is lowest at 20.07% per year in the biggest size quintile. All the MACD Sharpe ratios are higher than the buy & hold Sharpe ratio which are negative values in all 5 quintiles.

Panel B presents the results when short-sale constraint is imposed, that is when sell signal are generated investors are not allowed to take short position. We can clearly see the decreasing trend in both annual returns and Sharpe ratios as firm size increases. From the results the annual returns decreases monotonically from 21.13% in quintile 1 then decreases to 18.58%, 14.65%, 10.92% and 2.43% in quintile ,2,3,4 and 5 respectively. The Sharpe ratios also showing the same trend, the Sharpe ratio take value of 0.5976 in quintile 1 then decreases to 0.4249, 0.3495, 0.2560 and -0.1751 are the Sharpe ratios of the respective size quintile 2 to 5. The Sharpe ratios are also show the monotonic decreasing trend as firm size increases.

Both annual returns and Sharpe ratio are lower when short-sale constraint is imposed. This is because investors give up the returns from selling short when sell signal is emitted. From the results, returns during the sell period are negative for all 5 quintiles, the annual returns in sell period is -16.78% in quintile 1, -20.37% in quintiles 2, -11.376%,-10.256% and -7.645% in quintile 3, 4 and 5 respectively, Therefore if investors are allowed to take short position it means that they can reverse this negative returns into positive returns by selling short the indices when sell signal is emitted. This is some evidence that MACD strategy can identified the negative return period and positive return period.

From Table III, C is the implied break-even transaction cost that makes investors indifferent between MACD strategy and the naïve buy& hold strategy, the values present here are the percentage transaction cost per trade. In Thailand retail investors are charged 0.25% per trade, Therefore if the implied transaction cost is higher than 0.25% per trade it means the strategy results in economic profit. Without short-sale constraint imposed, the average breakeven cost is 0.99% for quintile 1 and 1.19% for quintile 2 and decreases to 0.73%, 0.66% and 0.39% in quintile 3, 4 and 5 respectively, again this average breakeven cost show the decreasing trend as firm size increases, indicates that MACD strategy results in higher economic profit in the smaller size quintiles.

When short-sale constraint is imposed, the breakeven transaction costs show the same decreasing trend as firm size increases. Note that the breakeven costs are not much different between with constraint case and without short-sale constraint case, in size quintile 1 it take values of 0.99% in both with and without short-sale constraint. Indicate that investors whose follows MACD strategy result in the very similar level of economic profit in both cases.

For the SET index and SET50 index, the results are also presented just to compare with the results from 5 size quintiles. The results from the 2 indices are very similar. When short-sale is allowed, the MACD annual returns are both positive which is 19.24% for SET index and 19.04% for SET50 index. , Sharpe ratios are higher than the buy & hold Sharpe ratio and the average break even transaction cost are 0.47% for SET index and 0.49% for SET 50 indicates that MACD strategy results in economic profit after transaction cost.

When short-sale is not allowed, as expected, both MACD annual returns and Sharpe ratio are still positive but lower than the case when investors can sell short the index, which is 12.84% for SET index and 12.46% for SET50 index, Sharpe ratios are still higher than the buy & hold Sharpe ratio which is at 0.5132 and 0.4349, it is interesting that, the average break even transaction costs are slightly higher in this case which is at 0.51% for both SET index and SET 50 index which still results in economic profit after transaction cost. A possible explanation is, when short-sale is not allowed investors will incur less transaction which deducts the profit earns from the sell signals. That makes the 2 cases result in more or less the same level of economic profit. Thus MACD strategy can identify the positive and negative return period like in the constructed 5 size quintiles.

DMA strategy across 5 quintiles

The results of all 12 DMA strategies varies in each quintile, thus finding an average return, Sharpe ratio and breakeven cost from all strategies in each quintile might not give us the good overall performance of DMA strategy in each quintile. For all 12 rules testing in this study, we notice that, increasing the number of short period moving average from 2 to 5 days results in slower signal and the consequences less number of emitted signals. In most cases increasing the number of short period moving average from 2 to 5 days results in poorer DMA performances compare with using 1 day as short period moving average, as measured by Sharpe ratio and the breakeven transaction cost. With short period equals to 5 days, on average across all 5 quintiles, average number of signal emitted for the whole 10 years sample period are only 8 signals or equals to 0.8 signals per year. Furthermore, most of the DMA strategies with short period equal to 5 days results in negative Sharpe ratio and negative breakeven transaction cost.

In our 5 size quintiles data set we find that DMA rules with and without band result in the same number of signals and performances, note that this results might be different when apply to other data set. However, trading rules use in this study is with 1% band. To save space the only the empirical results of DMA with 1 day short period moving average are presented here, results of the rest DMA strategy with 2 and 5 days as short period moving average are presented using the Bootstrap methodology. Results from DMA strategy are presented in table as follows, Table IV is the results of DMA (1, 50, 1) and (1, 100, 1) rule. Table V is the results of DMA (1, 150, 1) and (1, 200, 1) rule.

Panel A is the result when there is no short-sale constraint imposed. Panel B is the result with short-sale constraint. In the first column presents all parameters to evaluate trading rule performances, trading rule is written as short, long and band. The first row is the average number of trade per year, in second row 'Daily return' is the average daily return from the trading strategy follows with the third row 'Annual return' is the average annual return earns from each strategy. 'Annual sigma' is the standard deviation of return from DMA strategy. 'Annual sell return' is the return during the DMA sell period, negative annual sell return indicates the ability of DMA rules to identify the negative return period, 'BH sigma' is the standard deviation of return from the buy & hold strategy, 'round trip breakeven cost' is the average round-trip transaction cost that make investors indifferent between DMA strategy and the benchmark buy& bold strategy, if it is greater than the actual 0.5% round trip indicates the economic profit of the trading rule.

We can observe the decreasing trend of DMA strategies as firm size increases, although it does not shows the monotonic trend, however by comparing the smallest quintile with the largest quintile, there are 5 out of 8 rules (Excluded 5 days as short period) that DMA strategy showing this decreasing trend for both with and without short-sale constraint.

[Insert Table IV about here]

For DMA (1, 50, 1) results are presented in Table IV, without short-sale constraint, the results show the decreasing trend as firm size increases although it is not monotonic, that is for annual return is as high as 39.44% in the smallest quintile and decreases to19.66% ,12.13% and 6.76% for quintile 2,3 and 5 respectively. Sharpe ratio and breakeven transaction cost also showing this decreasing trend as firm size increases. Note that DMA (1, 50, 1) can identify the negative return period in quintile 1, 2, 3 and 5. The results are not monotonic in quintile 4, which DMA (1, 50, 1) has worst results. In this quintile 4 an annual return, Sharpe ratio and breakeven transaction cost are lower than the benchmark Buy & Hold strategy, it also can not identify negative return period in this quintile 4. The results are similar when short-sale constraint is imposed, that is the decreasing trend is not monotonic. However, by comparing the smallest quintile and biggest quintile we can see that the annual return, Sharpe ratio and breakeven transaction cost are decreases by comparing the smallest and the biggest quintile.

For DMA (1,100,1) results are presented in Table V, both with and without short-sale constraint case, in the original dataset, we can notice the decreasing trend in all measurements parameters as firm size increases. However the decreasing trend is not monotonic, in the case of no short-sale constraint, Sharpe ratio decreases from 0.8845 in quintile 1 to 0.0179 in quintile 2 then decreases to -0.9846 in quintile 5. The breakeven transaction cost also decreases from 14.54% per round trip in quintile 1 to 3.10% in quintile 2 where as -7.67% in quintile 5. When short-sale constraint is imposed, the results are similar, breakeven transaction cost is as high as 16.01% in the smallest quintile and decreases sharply to -10.36% in biggest quintile. Note that DMA (1, 100, 1) has ability to identify negative return period in size quintile 1, 2, 3 and 4 but not in the size quintile 5 which contains the largest firm size. The results indicate poor performance of this DMA (1, 100, 1) rule in the biggest size quintile, evidence from all of our evaluation parameters annual return and Sharpe ratio are all negative and lower than benchmark Buy & Hold strategy. Breakeven transaction costs are negative in both cases showing that it results in negative economic profit.

[Insert Table V about here]

For DMA (1,150,1) rule the results are presented in Table VI, we do not observe the clear decreasing trend in returns as firm size increases. By considering Sharpe ratio it suggests that DMA (1, 150,1) rule provides higher returns to investor in smaller size quintile stocks, for both with and without short-sale constraint. When short-sale is allowed, the Sharpe ratio in size quintile 1 and 2 are 0.1530 and 0.2457 respectively, which is greater than the Sharpe ratio in quintile 5 that takes value of 0.0171. Surprisingly, by considering the breakeven transaction cost between size quintile 1 and 5, the results shows reverse trend, breakeven transaction costs in quintile 5 are greater than the quintile 1 for both with and without short sale constraint. However, DMA (1, 150, 1) rule only has the ability to identify negative return period in smaller size quintile, specifically in size quintile 1 and 2.

For DMA (1, 200, 1) rule, the results are presented in Table VII. The result shows decreasing trend in Sharpe ratio and breakeven cost as firm size increases. Even though, the trend is not monotonic. By Sharpe ratio, it takes values of 0.2464 in size quintile 1 which is higher than the Buy Hold Sharpe ratio, while it is -0.6034 in size quintile 5 which is lower than the benchmark Buy Hold Sharpe ratio. In panel A, by considering breakeven transaction cost, the results show the same trend. It takes value of 4.54% in quintile 1 and 4.12% in quintile 2 which indicate the positive economic profit. While it results in negative economic profit in size quintile 3 and 5, the breakeven cost is -7.09% in quintile 3 and -6.10% in quintile 5. When short-sale is not allowed, in panel B, the breakeven cost is as high as 7.51% in quintile 1 while it decreases to 0.22% in quintile 5 which is lower than the actual 0.5% round-trip. Note that DMA (1, 200,1) has ability to identify negative return period in smaller quintile, quintile 1 and 2.

Results using Bootstrap Methodology

In order to implement the Bootstrap methodology, first we estimate parameters and collect residuals from the estimation under null models (EGARCH and GARCH (1, 1), then scrambles the residuals (sampling with replacement) for 500 times. The numbers of simulation used in this study follows *Brock et al (1992)*, which verified the reliability of the simulated p-value and find that, increasing the numbers of simulation more than 500 times increases only little to the reliability of simulated p-value.

Then we simulate the return series from estimated parameters and scrambled residuals, exponentiate the return series back to obtain 500 simulated index series for each size quintile. We then applying the DMA rules and MACD strategy to compute Sharpe ratio and breakeven transaction cost. To obtain empirical distributions of the Sharpe ratio and breakeven transaction cost for each size quintile. Simulated p-value is defined as fraction of the 500 simulations, which has value greater than the one in original return series. The mean values from simulation are also presented.

In order to emphasize robustness of results in our original data set, we consider statistical significance of Sharpe ratio and the breakeven transaction cost p-value. A statistically significant p-value (at the 5% level) means that, for at least 95% (475 out of 500) of the bootstrap simulation, Sharpe ratio from simulated return series is less than Sharpe ratio computed on original return series. As point out by *Brock et al (1992)*, this indicates that returns from the rules are not likely to have been generated from the null models, and thus provides strong support for the predictive ability of technical trading strategies.

[Insert Table VI about here]

Table VI presents Bootstrap results of MACD strategy under null model GARCH (1, 1). First we consider Buy & Hold returns and volatility, which is actually the market return and volatility. We can see that GARCH (1, 1) has good ability to explain return and volatility process in all 5 size quintiles. From simulated p-values the returns and volatilities are not significant different between original series and simulated series in all 5 size quintiles, only the p-value of 'Annual BH sigma' in quintile 3 is 0.074, shows significant difference at 10% confident level. It indicates that GARCH (1, 1) could not explain the volatility process in quintile 3 and that might be the explanation why simulated p-values of MACD returns, Sharpe ratio and breakeven cost in quintile 3 shows significant difference. Thus it might not be strong support for predictive ability of MACD in quintile 3 where null model could not well replicate volatility process. For the rest size quintiles 1, 2, 4 and 5 we find no strong support for MACD predictive ability. The simulated p-values of Sharpe ratio and breakeven cost in these 4 quintiles do not show any significant difference.

Bootstrap MACD results

[Insert Table VII about here]

EGARCH (1, 1) with Gaussian distribution, simulated p-value of buy & hold strategy zero in quintile 3, indicates that EGARCH could not explain the returns and volatility process in original quintile 3 return series. However, for quintile 1, 2, 4 and 5 the returns and volatility between original series and the simulations are not significant difference as suggests by simulated p-values. Indicates that EGARCH (1,1) with Gaussian distribution has good ability to explain returns and volatility process in quintile 1, 2, 4 and 5.

From all of the simulated p-values for an annual return, Sharpe ratio and breakeven cost in quintile 1, 2, 4 and 5 do not show significant differences between the value in original series and simulated series, thus it does not provides strong support for the predictive ability of MACD strategy.

After change the conditional distribution of residuals from Gaussian distribution to student's t distribution. We find that EGARCH (1, 1) with student's t distribution can explain the returns and volatility process in all 5 size quintiles. Buy & Hold returns and volatilities which are the market returns and market volatilities, it does not show significant difference between original series and the simulated series, as suggest by simulated p-values. For the ability of EGARCH model with student's t distribution to explain the returns generated by MACD strategy. From simulated p-value of MACD Sharpe ratio in quintile 1 is 0.014 (significant different at 5% confidence level), simulated p-value of breakeven cost is 0.88% (significant different at 10%), similar with simulated p-value when short-sale constraint is imposed, it also indicate significant difference between original and the simulations for MACD returns, Sharpe ratio and breakeven cost. Thus, it provides strong support for the predictive ability of MACD strategy in the smallest quintile.

[Insert Table VIII about here]

The results are similar in quintile 2, the returns from MACD are not likely to be generated from EGARCH (student's t) null model, also provide support for the predictive ability of MACD strategy in quintile 2.

For quintile 3, 4 and 5, the simulated p-values show that MACD returns, Sharpe ratio and the breakeven cost are not significant difference between original series and simulated series (at 10% confidence level). Thus, it does not provide strong support for the predictive ability of MACD strategy in quintile 3, 4 and 5. This shows some evidences that MACD strategy returns and predictive ability are decreasing as firm size increase, and support hypothesis that technical trading strategies are more appropriate in smaller stocks where information efficiency and information asymmetry are more pronounced.

Bootstrap DMA results

Since EGARCH (1, 1) with Gaussian distribution could not explain market returns and volatility process in quintile 3, therefore only the Bootstrap results under GARCH (1, 1) and EGARCH (1, 1) with student's t distribution are presented. Table IX presents the Bootstrap result under null model GARCH (1, 1). Panel A presents the result when short-sale is allowed. We can see that Bootstrap result provides support for the predictive ability of only 4 DMA rules in quintile 1. Simulated p-values of Sharpe ratio and breakeven cost of DMA (1, 50, 1), (1, 100, 1), (2, 50, 1) and (2, 100, 1) are significant difference, at 5% confident level for Sharpe ratio and at 10% confident level for breakeven cost. Sharpe ratio and breakeven cost of the rest 4 size quintiles 2, 3, 4 and 5 do not indicate significant difference between the original series and simulated series. Except DMA (5, 50, 1) rule in quintile 4, simulated p-value of both Sharpe ratio and breakeven cost are significant different (at 5% confidence level). The results are similar when short-sale constraint is imposed. Overall results provide strong support for predictive ability of only 4 out of 12 DMA rules and it is in the smallest size quintile.

[Insert Table IX about here]

[Insert Table X about here]

Table X presents the Bootstrap result under EGARCH (1, 1) with student's t distribution. Panel A presents the result without short-sale constraint imposed. DMA (1,50,1) and (1,100,1) Sharpe ratio and breakeven costs are significant difference, consistent with previous result under GARCH model. Sharpe ratio of DMA (1,50,1) rule has p-value equals to 0.002 significant difference at 5% confident level, breakeven cost p-value equals to 0.024 (at 5% confident level). For DMA (1, 100, 1) rule, p-value of Sharpe ratio equals to 0.008 (at 5% confident level), p-value of breakeven cost equals to 0.034 significant differences at 5% confident level. The results of DMA (1, 50, 1) and (1, 100, 1) are consistent with the previous null model, it support the predictive ability of this 2 DMA rules only in the same smallest size quintile. Sharpe ratio and breakeven cost p-values of DMA (5, 50, 1) are still significant in quintile 4, similar with previous GARCH (1, 1) null model. For DMA (2, 100, 1) rule p-values of Sharpe ratio and breakeven cost are significant different (10% confident level) only if short-sale constraint is imposed.

For DMA (2, 50, 1) rule, both Sharpe ratio and breakeven cost are not significant different under this null model EGARCH (1, 1), different from previous GARCH (1, 1) model. Overall results under EGARCH are consistent with previous null model GARCH (1, 1).

The major difference is the result of DMA (2, 50, 1) and (2, 100, 1) rules, which the predictive ability is not confirmed under EGARCH model. EGARCH result supports the predictive ability of 3 DMA rules (1, 50, 1), (1, 100, 1) and (2, 100, 1) in smallest quintile (when constraint imposed), predictive ability of the other DMA rules are not supported in the rest quintiles 2, 3, 4 and 5.

The Bootstrap results under GARCH and EGARCH null models suggest that, technical trading strategies MACD and DMA (3 out of 12 rules) have abilities to predict market movements and provide investors with higher risk-adjusted returns than benchmark Buy & Hold strategy, as measured by Sharpe ratio. After adjusting for transaction cost, technical trading rules still provide an economic profit to investors, as its breakeven transaction costs are higher than actual 0.25% per trade. However, its predictive ability are robust only in the smallest size quintile, suggest that technical trading strategies are more appropriate in the smaller size stocks.

Number of correct signals

The numbers of correct signals for the whole 10 years study period are examined separately between buy and sell signals. The correct signal is defined as the signal that provides positive return to investor (after 0.5% round trip transaction cost). When buy signal is generated, investor take long position on the next day (adjust for non-synchronous trading), hold that long position until sell signal is generated. That prior buy signal is counted as correct signal only if it provides positive return to investor. The same logic applies for sell signal. First column present the trading rules parameters, 'emitted' is the number of signals generated by technical trading rules, 'Buy tr' is the number of buy transactions taken, 'correct' is the numbers of correct signals. The last column '(%)' presents the percentage of correct signal, which is calculated as numbers of correct signals divided by number of transaction.

Table XI presents the result of correct buy signal. It is clearly seen that DMA rules generate very low number of signal compare to MACD strategy. For clear example, in quintile 5 DMA (5, 200, 1) emit only 1 buy signals for the whole 10 years (0.1 signal per year) while MACD generates 97 signals (9.7 signals per year).

[Insert Table XI about here]

[Insert Table XII about here]

We do not observe any decreasing trend in the percentage of correct signal across size quintiles. In quintile 1, MACD emits 87 buy signals, becomes 87 buy transactions and 37 buy signals are correct, which is equals to 42.5%. The percentages correct signals are very similar across 5 size quintile, MACD signals are correct 42.5% in quintile 1, 39.1% in quintile 2, 37.5% in quintile 3, 38.6% in quintile 4 and 35.1% in quintile 5. Similarly for DMA rules we also do not observe the decreasing trend in percentage correct signal as firm size increases.

The percentage correct signals are disperse among DMA rules, some DMA rules generate very high percentage correct signal but it is rather because of it has been generated very low number of signals for the whole period of 10 years. For example DMA (5, 50, 1) in quintile 4, which its predictive ability is confirmed by bootstrap results, it emit 3 buy signals (in 10 years), 2 buy transaction are taken and it is all correct similar with the sell signal, DMA (5, 50, 1) emits 5 sell signals (in 10 years), 2 short positions are taken and it is all correct.

It is important to note that DMA rules generate many redundant signals, which means that once buy (sell) signal is emitted DMA rules still emit many buy (sell) signals. From the result, number of buy or sell transactions rarely equal to the number of signal emitted for DMA rules. For example, DMA (1, 50, 1) rule in quintile 1 only 15 out of 23 buy signals are taken as long positions.

VI Conclusion

This paper investigates the predictive ability of 2 technical trading rules Moving Average Convergence Divergence (MACD) and Daily Moving Average (DMA) with different lengths of moving average periods on the 5 size quintiles constructed index. From the assumption, the improvement of market efficiency are not shared evenly across market segment, specifically small firms sizes, which has less information efficiency, accuracy and information asymmetry is more pronounced. *Blume, Easley and OHara (1994)* suggest that technical analysis may be more appropriate for smaller stocks than larger stocks. To evaluate the predictive ability of trading rules, we consider investors to be 'Risk-averse' that is to care about Risk-adjusted return rather than expected returns, Sharpe ratio is computed as a measurement for the risk-adjusted returns. Transaction costs are also included in this study, non-synchronous trading is recognized in this study, that is, buy (sell) position will take place on the day after signal date.

From the empirical results, for MACD we can clearly see the decreasing trends in the annual returns, Sharpe ratio and breakeven transaction cost as firm sizes increases, all of our measurements from MACD are higher than the benchmark buy & hold strategy, the results are similar when short-sale constraint is imposed. For DMA we find that not all of the DMA rules can provide returns higher than the benchmark buy & hold strategy, the results are dispersed across different moving average period used.

The predictive ability of those trading rules are emphasized by bootstrap methodology, the statistically significant difference between the Sharpe ratio or breakeven cost between the original series and the simulated series indicate that, returns from trading rules are not likely to be generated from null models, and Thus provide support for the predictive ability of particular trading rules. The predictive ability of MACD strategy is robust in quintile 1 and 2, which are the smaller quintiles. For all DMA 12 rules test, we find the evidences which support the predictive ability of DMA (1,50,1) and (1,100,1) rules, however, the results confirm the timing ability only in the smallest quintile.

To sum up, this paper examines empirical evidence that supports predictive ability of daily moving average and moving average convergence divergence strategy, however its predictive ability is not confirmed in all market segments. Its predictive ability is confirmed in small sizes stocks which have several characteristics that suggest it might be less efficient, it lack of analyst coverage, less in speed and accuracy of information and there are existence of information asymmetry. Improvements of market efficiency are not shared evenly across market. Specifically, market is less efficient in the segment that has smaller market capital and more efficient in the segment that has bigger market capital.

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Table I

Summary statistics for daily returns of all 5 size quintiles, returns are calculated as log difference of the level of size quintile index. D-stat is the test statistic for Kolmogorov-smirmov test of normality, $\rho(i)$ are the estimated autocorrelation at lag i for each period. 'Average Market Cap.' is 10 years average market capitalization of all stocks in each size quintile, 'Avg daily trading value' is 10 years average daily trading volume of all stocks in each size quintile.

	Quintile 1	*Quintile 2*	*Quintile 3*	*Quintile 4*	*Quintile 5*
Number of observations	2580	2580	2580	2580	2580
Average Mkt. Cap (MB)	550.38	1,653.25	4,115.42	11,391.49	65,714.88
Avg. Daily trading value (MB)	8.213	13.815	30.074	53.798	126.421
Daily mean return	0.0134%	-0.0104%	0.0103%	-0.0039%	-0.0203%
Standard Deviation	0.0231	0.0270	0.0233	0.0239	0.0132
Sample Variance	0.0005	0.0007	0.0005	0.0006	0.0002
Kurtosis	54.1092	205.1997	76.3743	101.3740	16.8486
Skewness	3.2333	-7.3199	1.7333	-1.3214	0.1990
D-stat (0.01)	0.4679	0.4680	0.4707	0.4694	0.4788
cut off value	0.0320	0.0320	0.0320	0.0320	0.0320
$\rho(1)$	0.1036	0.0596	0.0794	0.0341	0.0833
$\rho(2)$	0.0783	0.0487	0.0041	0.0473	0.0889
$\rho(3)$	0.0653	0.0000	-0.0188	0.0083	0.0326
$\rho(4)$	0.0198	0.0065	0.0089	-0.0190	0.0452

Table II

Estimation results for 5 size quintiles, EGARCH (1, 1) with student's t conditional distribution for residuals, estimation of model parameters and residuals are done by maximum log likelihood estimation.

Conditional Mean Equation

$$r_t = C + \phi r_{t-1} + \theta \varepsilon_{t-1} + \varepsilon_t$$

		C	AR	MA
Quintile 1	Coeff	-0.000241	0.45278	2.5977
	t-stat	-1.3001	2.5977	-2.0819
Quintile 2	Coeff	0.000060	0.82042	-0.78566
	t-stat	0.9351	10.6267	-9.3696
Quintile 3	Coeff	0.000020	0.93115	-0.91279
	t-stat	0.9207	21.6774	-19.0406
Quintile 4	Coeff	-0.000039	0.59838	-0.56902
	t-stat	-0.3462	2.3839	-2.209
Quintile 5	Coeff	0.000013	0.97229	-0.95172
	t-stat	1.3279	71.6669	-53.6915

* AR represent the autoregresstive coefficient ϕ

* MA represent the moving average coefficient θ

Conditional Variance equation
Distribution: T

$$\log \sigma_t^2 = K + G \log \sigma_{t-1}^2 + A \left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - E \left\{ \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} \right\} \right] + L \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right)$$

	K	GARCH	ARCH	L	DoF
Coeff	-0.22192	0.9717	0.18133	-0.053045	3.6453
t-stat	-4.1628	143.6826	8.8782	-4.0164	15.898
Coeff	-0.004272	0.99959	0.027513	0.0008599	3.7332
t-stat	-0.8235	1516.7568	4.9715	0.1887	18.547
Coeff	-0.010158	0.9989	0.066607	-0.006447	3.1007
t-stat	-1.2308	987.8885	6.6759	-0.9102	18.7996
Coeff	-0.034729	0.99577	0.058424	-0.013853	3.2472
t-stat	-2.3529	537.7958	7.1123	-2.2752	19.5963
Coeff	-0.037319	0.99578	0.086833	-0.008296	3.2696
t-stat	-1.7623	417.2964	0.086833	-0.9471	15.4327

* GARCH represent the coefficient G

* ARCH represent the coefficient A

* DoF represent the degree of freedom

Table III
Results of the MACD strategy for the 5 quintiles

‘Trade per year’ is the average number of trade made by strategy. ‘Breakeven cost’ is the average trading cost that make investor indifferent between technical trading strategy and benchmark Buy & Hold strategy.

Panel A: Without Short-sale constraint

MACD	quintile 1	quintile 2	quintile 3	quintile 4	quintile 5	SET	SET50
Trade per year	18	18	16	17	20	14	14
Daily return	0.00150	0.00154	0.00103	0.00084	0.00040	0.00095	0.00094
Annual return	38.01%	38.94%	26.02%	21.18%	10.07%	19.24%	19.04%
Annual Sigma	0.3630	0.4247	0.3660	0.3736	0.2070	0.2343	0.2600
Annual sell return	-16.88%	-20.37%	-11.38%	-10.26%	-7.64%	-6.40%	-6.58%
Sharpe ratio	0.9093	0.7993	0.5744	0.4331	0.2449	0.6079	0.5399
Breakeven cost per trade	0.99%	1.19%	0.73%	0.66%	0.39%	0.47%	0.49%

Panel B: With Short-sale constraint

MACD	quintile 1	quintile 2	quintile 3	quintile 4	quintile 5	SET	SET50
Trade per year	9	9	8	8	10	7	7
Daily return	0.00169	0.00143	0.00112	0.00086	0.00019	0.00125	0.00124
Annual return	21.13%	18.58%	14.65%	10.92%	2.43%	12.84%	12.46%
Annual Sigma	0.2699	0.2754	0.2760	0.2314	0.1471	0.1529	0.1716
Sharpe ratio	0.5976	0.4929	0.3495	0.2560	-0.1751	0.5132	0.4349
Breakeven cost per trade	0.99%	1.06%	0.71%	0.57%	0.24%	0.51%	0.51%

Buy & Hold	quintile 1	quintile 2	quintile 3	quintile 4	quintile 5	SET	SET50
Daily return	0.00013	-0.00010	0.00010	-0.00004	-0.00020	0.00028	0.00026
Annual BH return	3.45%	-2.69%	2.65%	-1.02%	-5.24%	5.86%	5.36%
Annual BH sigma	0.3655	0.4275	0.3689	0.3785	0.2082	0.2428	0.2703
Sharpe ratio	-0.0424	-0.1799	-0.0638	-0.1590	-0.4919	0.0353	0.0134

Table IV: DMA (1, 50,1) and (1,100,1) results across 5 size quintiles

Panel A: Without Short-sale constraint

DMA (1,50,1)	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Trade per year	3.1	2.6	3	3.2	1.7
Daily return	0.00159	0.00081	0.00050	-0.00040	0.00030
Annual return	39.44%	19.66%	12.13%	-10.07%	6.76%
Annual Sigma	0.3567	0.4146	0.3599	0.3743	0.1782
Annual sell return	-16.27%	-9.95%	-4.61%	5.61%	-1.51%
Sharpe ratio	0.9656	0.3536	0.1980	-0.4026	0.0988
round trip breakeven cost	11.60%	8.51%	3.14%	-2.85%	6.19%

Panel B: With Short-sale constraint

DMA (1,50,1)	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Trade per year	1.6	1.3	1.5	1.6	0.8
Daily return	0.00222	0.00087	0.00071	-0.00042	0.00056
Annual return	23.17%	9.71%	7.51%	-4.46%	5.25%
Annual Sigma	0.2621	0.2861	0.2322	0.2658	0.1125
Sharpe ratio	0.6935	0.1646	0.1082	-0.3559	0.0219
round trip breakeven cost	12.05%	7.58%	2.66%	-3.27%	7.23%

Benchmark Buy & Hold strategy

Buy & Hold	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Daily return	0.00013	-0.00010	0.00010	-0.00004	-0.00020
Annual BH return	3.45%	-2.69%	2.65%	-1.02%	-5.24%
Annual BH sigma	0.3655	0.4275	0.3689	0.3785	0.2082
Sharpe ratio	-0.0424	-0.1799	-0.0638	-0.1590	-0.4919

Panel A: Without Short-sale constraint

DMA (1,100,1)	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Trade per year	2.2	2.7	2.4	2	1.3
Daily return	0.00142	0.00023	0.00037	0.00008	-0.00060
Annual return	35.46%	5.76%	8.74%	2.05%	-14.93%
Annual Sigma	0.3606	0.4236	0.3350	0.3714	0.2024
Annual sell return	-14.04%	-2.60%	-0.76%	-0.28%	5.15%
Sharpe ratio	0.8445	0.0179	0.1115	-0.0795	-0.9846
round trip breakeven cost	14.54%	3.10%	2.45%	1.48%	-7.67%

Panel B: With Short-sale constraint

DMA (1,100,1)	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Trade per year	1.1	1.3	1.2	1	0.7
Daily return	0.00146	0.00034	0.00072	0.00013	-0.00116
Annual return	21.42%	3.16%	7.97%	1.77%	-9.78%
Annual Sigma	0.2811	0.2951	0.2073	0.2962	0.1530
Sharpe ratio	0.5841	-0.0624	0.1433	-0.1090	-0.9657
round trip breakeven cost	16.01%	2.67%	3.58%	1.48%	-10.36%

Benchmark Buy & Hold strategy

Buy & Hold	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Daily return	0.00013	-0.00010	0.00010	-0.00004	-0.00020
Annual BH return	3.45%	-2.69%	2.65%	-1.02%	-5.24%
Annual BH sigma	0.3655	0.4275	0.3689	0.3785	0.2082
Sharpe ratio	-0.0424	-0.1799	-0.0638	-0.1590	-0.4919

Table V: DMA (1, 150, 1) and (1, 200, 1) results across 5 size quintiles

Panel A: Without Short-sale constraint

DMA (1,150,1)	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Trade per year	2.6	2.5	1.3	2	1.1
Daily return	0.00043	0.00062	-0.00005	-0.00061	0.00025
Annual return	10.07%	15.19%	-1.07%	-14.99%	5.29%
Annual Sigma	0.3313	0.4147	0.3324	0.3689	0.1676
Annual sell return	-0.28%	-7.66%	3.04%	8.65%	0.89%
Sharpe ratio	0.1530	0.2457	-0.1828	-0.5418	0.0171
round trip breakeven cost	2.49%	7.06%	-3.04%	-7.06%	7.76%

Panel B: With Short-sale constraint

DMA (1,150,1)	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Trade per year	1.3	1.2	0.7	1	0.6
Daily return	0.00079	0.00068	0.00022	-0.00043	0.00065
Annual return	9.79%	7.53%	1.96%	-6.33%	6.18%
Annual Sigma	0.2536	0.3126	0.1968	0.2738	0.1091
Sharpe ratio	0.1888	0.0811	-0.1543	-0.4139	0.1082
round trip breakeven cost	4.51%	6.80%	-2.54%	-6.98%	10.91%

Benchmark Buy & Hold strategy

Buy & Hold	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Daily return	0.00013	-0.00010	0.00010	-0.00004	-0.00020
Annual BH return	3.45%	-2.69%	2.65%	-1.02%	-5.24%
Annual BH sigma	0.3655	0.4275	0.3689	0.3785	0.2082
Sharpe ratio	-0.0424	-0.1799	-0.0638	-0.1590	-0.4919

Panel A: Without Short-sale constraint

DMA (1,200,1)	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Trade per year	2.1	2	2.3	1.3	0.3
Daily return	0.00057	0.00027	-0.00056	0.00006	-0.00024
Annual return	13.13%	6.34%	-13.59%	1.42%	-4.90%
Annual Sigma	0.3299	0.3835	0.3579	0.3681	0.1640
Annual sell return	-1.61%	-2.65%	9.68%	1.00%	5.96%
Sharpe ratio	0.2464	0.0350	-0.5192	-0.0971	-0.6034
round trip breakeven cost	4.54%	4.12%	-7.09%	1.75%	-6.10%

Panel B: With Short-sale constraint

DMA (1,200,1)	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Trade per year	1	1	1.1	0.7	0.2
Daily return	0.00112	0.00033	-0.00027	0.00024	0.00019
Annual return	11.52%	3.69%	-3.90%	2.42%	1.07%
Annual Sigma	0.2317	0.2982	0.2603	0.2343	0.0809
Sharpe ratio	0.2816	-0.0440	-0.3420	-0.1101	-0.4864
round trip breakeven cost	7.51%	4.05%	-6.58%	1.64%	0.22%

Benchmark Buy & Hold strategy

Buy & Hold	*quintile 1*	*quintile 2*	*quintile 3*	*quintile 4*	*quintile 5*
Daily return	0.00013	-0.00010	0.00010	-0.00004	-0.00020
Annual BH return	3.45%	-2.69%	2.65%	-1.02%	-5.24%
Annual BH sigma	0.3655	0.4275	0.3689	0.3785	0.2082
Sharpe ratio	-0.0424	-0.1799	-0.0638	-0.1590	-0.4919

Table VI
Results from Bootstrap methodology, null model GARCH (1, 1).

‘Simulated p-value’ is the fraction that values from simulated series larger than that from original series. A statistically significant p-value indicates that returns from trading rules are not likely to have been generated from null model, and thus provides strong support for the predictive ability of technical trading strategy.

GARCH (1,1)

Panel A: Without Short-sale constraint

MACD	quintile 1			quintile 2			quintile 3			quintile 4			quintile 5		
	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value
Trade per year	17.5	17.6		17.5	18.1		16.1	19.1		16.8	18.5		19.5	17.9	
Daily return	0.00150	0.00130	0.320	0.00154	0.00086	0.118	0.00103	0.00013	0.012**	0.00084	0.00045	0.202	0.00040	0.00041	0.526
Annual return	38.01%	32.99%	0.320	38.94%	21.70%	0.118	26.02%	3.42%	0.012**	21.18%	11.49%	0.202	10.07%	10.37%	0.522
Annual Sigma	0.3630	0.3748	0.424	0.4247	0.4161	0.406	0.3660	0.2416	0.076*	0.3736	0.3821	0.524	0.2070	0.2082	0.424
Annual sell return	-16.88%	-15.13%	0.590	-20.37%	-12.80%	0.760	-11.38%	-0.63%	0.952**	-10.26%	-7.00%	0.636	-7.64%	-8.69%	0.440
Sharpe ratio	0.9093	0.7527	0.326	0.7993	0.4082	0.134	0.5744	-0.0919	0.030**	0.4331	0.1698	0.212	0.2449	0.2594	0.516
Breakeven cost per trade	0.99%	0.88%	0.400	1.19%	0.74%	0.226	0.73%	0.04%	0.030**	0.66%	0.40%	0.310	0.39%	0.50%	0.594

Panel B: With Short-sale constraint

MACD	quintile 1			quintile 2			quintile 3			quintile 4			quintile 5		
	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value
Trade per year	8.7	8.8		8.7	9.1		8.0	9.6		8.4	9.3		9.7	9.0	
Daily return	0.00169	0.00137	0.330	0.00143	0.00068	0.164	0.00112	0.00022	0.034**	0.00086	0.00036	0.242	0.00019	0.00013	0.464
Annual return	21.13%	17.87%	0.358	18.58%	8.90%	0.170	14.65%	2.79%	0.032**	10.92%	4.49%	0.250	2.43%	1.67%	0.468
Annual Sigma	0.2699	0.2699	0.352	0.2754	0.2988	0.532	0.2760	0.1710	0.066*	0.2314	0.2704	0.798	0.1471	0.1492	0.470
Sharpe ratio	0.5976	0.4583	0.374	0.4929	0.1602	0.168	0.3495	-0.1599	0.072*	0.2560	-0.0171	0.222	-0.1751	-0.2376	0.466
Breakeven cost per trade	0.99%	0.84%	0.344	1.06%	0.60%	0.158	0.71%	0.00%	0.014**	0.57%	0.28%	0.200	0.24%	0.30%	0.592

Buy & Hold	quintile 1			quintile 2			quintile 3			quintile 4			quintile 5		
	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value
Daily return	0.00013	0.00011	0.456	-0.00010	-0.00016	0.456	0.00010	0.00009	0.470	-0.00004	-0.00010	0.478	-0.00020	-0.00027	0.450
Annual BH return	3.45%	2.77%	0.456	-2.69%	-4.11%	0.456	2.65%	2.23%	0.470	-1.02%	-2.62%	0.478	-5.24%	-7.09%	0.450
Annual BH sigma	0.3655	0.3800	0.432	0.4275	0.4206	0.418	0.3689	0.2435	0.074*	0.3785	0.3857	0.516	0.2082	0.2101	0.436
Sharpe ratio	-0.0424	-0.0880	0.458	-0.1799	-0.1999	0.450	-0.0638	-0.1268	0.426	-0.1590	-0.1975	0.478	-0.4919	-0.5868	0.456

****** represents statistical significant difference at 5% confident level

***** represents statistical significant difference at 10% confident level

Table VII
Results from Bootstrap methodology, null model EGARCH (1, 1) with Gaussian distribution.

‘Simulated p-value’ is the fraction that values from simulated series larger than that from original series. A statistically significant p-value indicates that returns from trading rules are not likely to have been generated from null model, and thus provides strong support for the predictive ability of technical trading strategy.

EGARCH (1,1) Gaussian distribution

Panel A: Without Short-sale constraint

MACD	quintile 1			quintile 2			quintile 3			quintile 4			quintile 5		
	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value
Trade per year	17.5	18.1		17.5	17.9		16.1	19.1		16.8	18.6		19.5	17.7	
Daily return	0.00150	0.00082	0.074*	0.00154	0.00082	0.098*	0.00103	0.00008	0.000**	0.00084	0.00038	0.192	0.00040	0.00045	0.562
Annual return	38.01%	20.79%	0.072*	38.94%	20.68%	0.100	26.02%	2.07%	0.000**	21.18%	9.56%	0.192	10.07%	11.46%	0.558
Annual Sigma	0.3630	0.3003	0.128	0.4247	0.4197	0.420	0.3660	0.1463	0.004**	0.3736	0.3772	0.506	0.2070	0.2052	0.392
Annual sell return	-16.88%	-9.11%	0.826	-20.37%	-11.63%	0.802	-11.38%	-2.51%	0.978	-10.26%	-6.67%	0.664	-7.64%	-9.01%	0.430
Sharpe ratio	0.9093	0.5196	0.128	0.7993	0.3765	0.100	0.5744	-0.2490	0.014**	0.4331	0.1200	0.196	0.2449	0.3175	0.560
Breakeven cost per trade	0.99%	0.52%	0.156	1.19%	0.68%	0.200	0.73%	0.14%	0.012**	0.66%	0.38%	0.292	0.39%	0.53%	0.600

Panel B: With Short-sale constraint

MACD	quintile 1			quintile 2			quintile 3			quintile 4			quintile 5		
	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value
Trade per year	8.7	9.1		8.7	9.0		8.0	9.5		8.4	9.3		9.7	8.8	
Daily return	0.00169	0.00092	0.110	0.00143	0.00069	0.188	0.00112	-0.00003	0.000**	0.00086	0.00023	0.202	0.00019	0.00019	0.502
Annual return	21.13%	11.68%	0.114	18.58%	9.05%	0.202	14.65%	-0.45%	0.000**	10.92%	2.88%	0.200	2.43%	2.45%	0.504
Annual Sigma	0.2699	0.2134	0.110	0.2754	0.3006	0.516	0.2760	0.1033	0.004**	0.2314	0.2711	0.798	0.1471	0.1500	0.494
Sharpe ratio	0.5976	0.3111	0.208	0.4929	0.1700	0.200	0.3495	-0.5810	0.000**	0.2560	-0.0780	0.172	-0.1751	-0.1733	0.510
Breakeven cost per trade	0.99%	0.49%	0.098*	1.06%	0.56%	0.118	0.71%	0.01%	0.002**	0.57%	0.24%	0.196	0.24%	0.35%	0.632

Buy & Hold	quintile 1			quintile 2			quintile 3			quintile 4			quintile 5		
	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value
Daily return	0.00013	0.00010	0.478	-0.00010	-0.00010	0.524	0.00010	-0.00012	0.000**	-0.00004	-0.00015	0.430	-0.00020	-0.00026	0.458
Annual BH return	3.45%	2.54%	0.478	-2.69%	-2.67%	0.524	2.65%	-3.00%	0.000**	-1.02%	-3.83%	0.430	-5.24%	-6.66%	0.458
Annual BH sigma	0.3655	0.3027	0.130	0.4275	0.4243	0.442	0.3689	0.1483	0.002**	0.3785	0.3804	0.496	0.2082	0.2069	0.406
Sharpe ratio	-0.0424	-0.0776	0.470	-0.1799	-0.1597	0.510	-0.0638	-0.5455	0.000**	-0.1590	-0.2333	0.428	-0.4919	-0.5677	0.460

** represents statistical significant difference at 5% confident level

* represents statistical significant difference at 10% confident level

Table VIII

Results from Bootstrap methodology, null model EGARCH (1, 1) with student's t distribution.

'Simulated p-value' is the fraction that values from simulated series larger than that from original series. A statistically significant p-value indicates that returns from trading rules are not likely to have been generated from null model, and thus provides strong support for the predictive ability of technical trading strategy.

EGARCH (1,1) Student's t distribution ***Panel A: Without Short-sale constraint***

MACD	quintile 1			quintile 2			quintile 3			quintile 4			quintile 5		
	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value
Trade per year	17.5	19.0		17.5	18.2		16.1	18.3		16.8	18.9		19.5	18.7	
Daily return	0.0015	0.0005	0.036**	0.0015	0.0005	0.032**	0.0010	0.0004	0.126	0.0008	0.0003	0.182	0.0004	0.0003	0.350
Annual return	38.01%	11.88%	0.036**	38.94%	12.28%	0.032**	26.02%	11.31%	0.126	21.18%	8.30%	0.180	10.07%	7.37%	0.350
Annual Sigma	0.3630	0.4037	0.622	0.4247	0.2742	0.152	0.3660	0.4071	0.376	0.3736	0.4676	0.672	0.2070	0.2327	0.584
Annual sell return	-16.88%	-4.20%	0.896	-20.37%	-5.57%	0.926	-11.38%	-5.56%	0.786	-10.26%	-4.68%	0.700	-7.64%	-4.08%	0.710
Sharpe ratio	0.9093	0.1675	0.014**	0.7993	0.2367	0.042**	0.5744	0.1199	0.110	0.4331	0.0593	0.112	0.2449	0.0956	0.330
Breakeven cost per trade	0.99%	0.23%	0.088*	1.19%	0.32%	0.074*	0.73%	0.33%	0.196	0.66%	0.27%	0.246	0.39%	0.23%	0.298

Panel B: With Short-sale constraint

MACD	quintile 1			quintile 2			quintile 3			quintile 4			quintile 5		
	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value
Trade per year	8.7	9.5		8.7	9.1		8	9.2		8.4	9.4		9.7	9.3	
Daily return	0.0017	0.0006	0.084*	0.0014	0.0005	0.058*	0.0011	0.0005	0.176	0.0009	0.0003	0.232	0.0002	0.0003	0.574
Annual return	21.13%	7.67%	0.092*	18.58%	6.71%	0.058*	14.65%	5.75%	0.172	10.92%	3.62%	0.238	2.43%	3.29%	0.574
Annual Sigma	0.2699	0.2804	0.504	0.2754	0.1942	0.170	0.2760	0.3009	0.356	0.2314	0.3314	0.766	0.1471	0.1673	0.600
Sharpe ratio	0.598	0.072	0.066*	0.493	0.154	0.174	0.349	0.040	0.214	0.256	-0.061	0.184	-0.175	-0.090	0.572
Breakeven cost per trade	0.99%	0.19%	0.040**	1.06%	0.26%	0.058*	0.71%	0.27%	0.136	0.57%	0.18%	0.166	0.24%	0.14%	0.308

Buy & Hold	quintile 1			quintile 2			quintile 3			quintile 4			quintile 5		
	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value	original	mean	p-value
Daily return	0.00013	0.00014	0.506	-0.00010	0.00005	0.696	0.00010	0.00001	0.524	-0.00004	-0.00005	0.502	-0.00020	-0.00003	0.672
Annual BH return	3.45%	3.69%	0.506	-2.69%	1.18%	0.696	2.65%	0.29%	0.524	-1.02%	-1.20%	0.502	-5.24%	-0.77%	0.672
Annual BH sigma	0.3655	0.4096	0.638	0.4275	0.2764	0.156	0.3689	0.4094	0.370	0.3785	0.4712	0.674	0.2082	0.2344	0.594
Sharpe ratio	-0.0424	-0.0472	0.508	-0.1799	-0.0430	0.604	-0.0638	-0.0595	0.504	-0.1590	-0.1404	0.516	-0.4919	-0.2239	0.696

****** represents statistical significant difference at 5% confident level

***** represents statistical significant difference at 10% confident level

Table IX

'Sharpe' represents Sharpe ratio, 'C' represents implied breakeven transaction cost (round-trip), and fractions that values from simulated series are larger than that from original series are considered as simulated p-value.

GARCH (1,1)

Panel A: without short-sale constraint

	T1		T2		T3		T4		T5	
DMA rules	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value
1,50,1	0.966	0.030**	0.354	0.256	0.198	0.152	-0.403	0.890	0.099	0.586
1,100,1	0.844	0.030**	0.018	0.536	0.112	0.214	-0.080	0.512	-0.985	0.960
1,150,1	0.153	0.410	0.246	0.282	-0.183	0.486	-0.542	0.924	0.017	0.556
1,200,1	0.246	0.334	0.035	0.492	-0.519	0.808	-0.097	0.522	-0.603	0.878
2,50,1	0.966	0.030**	0.354	0.256	0.198	0.152	-0.403	0.890	0.099	0.586
2,100,1	0.844	0.030**	0.018	0.536	0.112	0.214	-0.080	0.512	-0.985	0.960
2,150,1	0.153	0.410	0.246	0.282	-0.183	0.486	-0.542	0.924	0.017	0.556
2,200,1	0.246	0.334	0.035	0.492	-0.519	0.808	-0.097	0.522	-0.603	0.878
5,50,1	-0.481	0.844	-0.108	0.556	-0.298	0.796	0.687	0.016**	-0.303	0.832
5,100,1	-0.288	0.688	-0.769	0.960	-0.518	0.914	-0.249	0.666	-0.616	0.950
5,150,1	-0.335	0.766	-0.155	0.576	-0.155	0.730	0.066	0.290	0.000	0.100
5,200,1	-0.163	0.660	-0.164	0.578	-0.277	0.850	-0.204	0.634	-0.113	0.892
Buy & Hold	-0.0424	0.458	-0.1799	0.450	-0.0638	0.426	-0.1590	0.478	-0.4919	0.456

	T1		T2		T3		T4		T5	
DMA rules	C	p-value	C	p-value	C	p-value	C	p-value	C	p-value
1,50,1	11.60%	0.076*	8.51%	0.148	3.14%	0.194	-2.85%	0.864	6.19%	0.566
1,100,1	14.54%	0.090*	3.10%	0.482	2.45%	0.288	1.48%	0.494	-7.67%	0.932
1,150,1	2.49%	0.474	7.06%	0.358	-3.04%	0.608	-7.06%	0.914	7.76%	0.606
1,200,1	4.54%	0.394	4.12%	0.512	-7.09%	0.762	1.75%	0.492	-6.10%	0.872
2,50,1	11.60%	0.076*	8.51%	0.148	3.14%	0.194	-2.85%	0.864	6.19%	0.566
2,100,1	14.54%	0.090*	3.10%	0.482	2.45%	0.288	1.48%	0.494	-7.67%	0.932
2,150,1	2.49%	0.474	7.06%	0.358	-3.04%	0.608	-7.06%	0.914	7.76%	0.606
2,200,1	4.54%	0.394	4.12%	0.512	-7.09%	0.762	1.75%	0.492	-6.10%	0.872
5,50,1	-17.38%	0.770	3.33%	0.546	-10.71%	0.770	78.99%	0.014**	12.78%	0.260
5,100,1	-16.56%	0.700	-49.10%	0.954	-27.54%	0.894	-5.59%	0.680	-5.23%	0.912
5,150,1	-48.28%	0.886	2.02%	0.536	-6.05%	0.766	16.04%	0.326	0.00%	0.152
5,200,1	-6.10%	0.614	2.79%	0.464	-10.92%	0.848	-3.97%	0.622	37.73%	0.088*

Panel B: With short-sale constraint

	T1		T2		T3		T4		T5	
DMA rules	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value
1,50,1	0.693	0.076*	0.165	0.256	0.108	0.156	-0.356	0.726	0.022	0.292
1,100,1	0.584	0.078*	-0.062	0.410	0.143	0.124	-0.109	0.422	-0.966	0.854
1,150,1	0.189	0.314	0.081	0.274	-0.154	0.372	-0.414	0.742	0.108	0.194
1,200,1	0.282	0.212	-0.044	0.380	-0.342	0.544	-0.110	0.374	-0.486	0.552
2,50,1	0.693	0.076*	0.165	0.256	0.108	0.156	-0.356	0.726	0.022	0.292
2,100,1	0.584	0.078*	-0.062	0.410	0.143	0.124	-0.109	0.422	-0.966	0.854
2,150,1	0.189	0.314	0.081	0.274	-0.154	0.372	-0.414	0.742	0.108	0.194
2,200,1	0.282	0.212	-0.044	0.380	-0.342	0.544	-0.110	0.374	-0.486	0.552
5,50,1	-0.332	0.704	-0.164	0.466	-0.246	0.698	0.516	0.026**	-0.570	0.766
5,100,1	-0.066	0.480	-0.653	0.900	-0.309	0.760	-0.231	0.490	-0.331	0.784
5,150,1	-0.101	0.544	-0.256	0.546	-0.110	0.662	-0.034	0.324	0.000	0.032**
5,200,1	-0.034	0.482	-0.129	0.418	-0.202	0.780	-0.150	0.414	-0.404	0.866
Buy & Hold	-0.0424	0.458	-0.1799	0.450	-0.0638	0.426	-0.1590	0.478	-0.4919	0.456

	T1		T2		T3		T4		T5	
DMA rules	C	p-value	C	p-value	C	p-value	C	p-value	C	p-value
1,50,1	12.05%	0.040**	7.58%	0.074*	2.66%	0.104	-3.27%	0.908	7.23%	0.298
1,100,1	16.01%	0.038**	2.67%	0.438	3.58%	0.122	1.48%	0.364	-10.36%	0.944
1,150,1	4.51%	0.306	6.80%	0.226	-2.54%	0.492	-6.98%	0.908	10.91%	0.362
1,200,1	7.51%	0.230	4.05%	0.356	-6.58%	0.654	1.64%	0.370	0.22%	0.634
2,50,1	12.05%	0.040**	7.58%	0.074*	2.66%	0.104	-3.27%	0.908	7.23%	0.298
2,100,1	16.01%	0.038**	2.67%	0.438	3.58%	0.122	1.48%	0.364	-10.36%	0.944
2,150,1	4.51%	0.306	6.80%	0.226	-2.54%	0.492	-6.98%	0.908	10.91%	0.362
2,200,1	7.51%	0.230	4.05%	0.356	-6.58%	0.654	1.64%	0.370	0.22%	0.634
5,50,1	-13.06%	0.694	1.06%	0.514	-11.16%	0.700	69.50%	0.006*	-5.38%	0.820
5,100,1	-1.98%	0.484	-46.04%	0.950	-15.45%	0.778	-6.62%	0.604	9.60%	0.116
5,150,1	-17.80%	0.690	-8.27%	0.628	-3.57%	0.680	8.21%	0.290	0.00%	0.102
5,200,1	0.79%	0.328	13.11%	0.272	-10.25%	0.802	1.57%	0.310	10.51%	0.090*

****** represents statistical significant difference at 5% confident level

* represents statistical significant difference at 10% confident level

Table X

‘Sharpe’ represents Sharpe ratio, ‘C’ represents implied breakeven transaction cost (round-trip), and fractions that values from simulated series are larger than that from original series are considered as simulated p-value.

EGARCH (1,1)_student's t distribution

Panel A: without short-sale constraint

	T1		T2		T3		T4		T5	
DMA rules	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value
1,50,1	0.966	0.002**	0.354	0.156	0.198	0.372	-0.403	0.858	0.099	0.526
1,100,1	0.844	0.008**	0.018	0.386	0.112	0.440	-0.080	0.508	-0.985	0.974
1,150,1	0.153	0.334	0.246	0.170	-0.183	0.674	-0.542	0.892	0.017	0.560
1,200,1	0.246	0.232	0.035	0.314	-0.519	0.884	-0.097	0.516	-0.603	0.894
2,50,1	-0.167	0.668	0.182	0.246	-0.125	0.664	0.055	0.346	0.130	0.474
2,100,1	0.437	0.102	-0.143	0.588	-0.094	0.616	-0.248	0.662	-0.775	0.930
2,150,1	-0.266	0.688	-0.275	0.692	0.014	0.408	-0.492	0.836	-0.235	0.716
2,200,1	0.066	0.334	-0.096	0.598	0.037	0.392	0.065	0.342	0.000	0.368
5,50,1	-0.481	0.860	-0.108	0.732	-0.298	0.792	0.687	0.008**	-0.303	0.810
5,100,1	-0.166	0.658	-0.491	0.944	-0.275	0.860	-0.056	0.586	-0.052	0.870
5,150,1	0.019	0.434	-0.006	0.818	0.024	0.254	0.043	0.222	0.000	0.154
5,200,1	-0.034	0.498	-0.129	0.760	-0.202	0.764	-0.150	0.572	-0.404	0.896
BH sharp	-0.0424	0.592	-0.1799	0.822	-0.0638	0.738	-0.1590	0.696	-0.4919	0.908

	T1		T2		T3		T4		T5	
DMA rules	C	p-value	C	p-value	C	p-value	C	p-value	C	p-value
1,50,1	11.60%	0.024**	8.51%	0.100	3.14%	0.420	-2.85%	0.766	6.19%	0.426
1,100,1	14.54%	0.034**	3.10%	0.334	2.45%	0.492	1.48%	0.442	-7.67%	0.838
1,150,1	2.49%	0.380	7.06%	0.246	-3.04%	0.640	-7.06%	0.758	7.76%	0.482
1,200,1	4.54%	0.302	4.12%	0.312	-7.09%	0.728	1.75%	0.424	-6.10%	0.754
2,50,1	-2.51%	0.638*	8.93%	0.238	-1.49%	0.628	4.72%	0.332	21.04%	0.274
2,100,1	16.39%	0.104	0.83%	0.360	-0.92%	0.594	-2.76%	0.540	-9.70%	0.758
2,150,1	-6.20%	0.634	-3.96%	0.638	2.34%	0.416	-17.00%	0.824	8.58%	0.398
2,200,1	2.56%	0.358	3.44%	0.294	3.26%	0.418	6.87%	0.372	0.00%	0.464
5,50,1	-17.38%	0.722	3.33%	0.262	-10.71%	0.704	78.99%	0.026**	12.78%	0.276
5,100,1	3.36%	0.414	-14.06%	0.964	-0.84%	0.758	-1.38%	0.612	1.04%	0.194
5,150,1	-10.09%	0.496	-25.58%	0.786	-10.99%	0.672	-3.37%	0.434	0.00%	0.072*
5,200,1	0.79%	0.282	13.11%	0.082	-10.25%	0.756	1.57%	0.216	10.51%	0.084*

Panel B: With short-sale constraint

	T1		T2		T3		T4		T5	
DMA rules	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value	Sharpe	p-value
1,50,1	0.693	0.018**	0.165	0.244	0.108	0.358	-0.356	0.748	0.022	0.414
1,100,1	0.584	0.038**	-0.062	0.402	0.143	0.310	-0.109	0.450	-0.966	0.920
1,150,1	0.189	0.258	0.081	0.236	-0.154	0.548	-0.414	0.768	0.108	0.302
1,200,1	0.282	0.160	-0.044	0.356	-0.342	0.704	-0.110	0.432	-0.486	0.666
2,50,1	-0.151	0.616	0.036	0.282	-0.095	0.560	-0.034	0.368	-0.315	0.592
2,100,1	0.452	0.074	-0.170	0.506	-0.078	0.488	-0.258	0.604	-0.959	0.906
2,150,1	0.073	0.286	-0.550	0.850	0.016	0.346	-0.330	0.640	-0.049	0.450
2,200,1	0.112	0.272	-0.222	0.602	0.030	0.282	0.011	0.284	0.000	0.214
5,50,1	-0.332	0.694	-0.164	0.666	-0.246	0.688	0.516	0.032**	-0.570	0.812
5,100,1	-0.020	0.420	-0.460	0.940	-0.154	0.784	-0.066	0.526	0.096	0.144
5,150,1	0.035	0.462	-0.027	0.826	0.026	0.282	-0.010	0.652	0.000	0.124
5,200,1	-0.042	0.592	-0.180	0.822	-0.064	0.738	-0.159	0.696	-0.492	0.908
BH sharp	-0.0424	0.592	-0.1799	0.822	-0.0638	0.738	-0.1590	0.696	-0.4919	0.908

	T1		T2		T3		T4		T5	
DMA rules	C	p-value	C	p-value	C	p-value	C	p-value	C	p-value
1,50,1	12.05%	0.004**	7.58%	0.056*	2.66%	0.394	-3.27%	0.788	7.23%	0.248
1,100,1	16.01%	0.004**	2.67%	0.288	3.58%	0.390	1.48%	0.334	-10.36%	0.858
1,150,1	4.51%	0.220	6.80%	0.174	-2.54%	0.582	-6.98%	0.764	10.91%	0.282
1,200,1	7.51%	0.126	4.05%	0.228	-6.58%	0.690	1.64%	0.306	0.22%	0.528
2,50,1	-2.53%	0.632	6.41%	0.208	-1.22%	0.586	4.17%	0.246	6.23%	0.414
2,100,1	29.55%	0.006**	0.33%	0.320	-0.57%	0.538	-4.07%	0.544	-19.59%	0.826
2,150,1	4.72%	0.252	-11.14%	0.698	3.34%	0.340	-13.78%	0.762	27.43%	0.144
2,200,1	6.14%	0.218	-1.59%	0.576	4.46%	0.318	5.51%	0.260	0.00%	0.356
5,50,1	-13.06%	0.660	1.06%	0.208	-11.16%	0.706	69.50%	0.018**	-5.38%	0.748
5,100,1	3.45%	0.486	-2.69%	0.792	2.65%	0.298	-1.02%	0.614	-5.24%	0.832
5,150,1	-4.24%	0.554	-17.99%	0.804	-6.38%	0.696	-15.90%	0.668	0.00%	0.088*
5,200,1	36.55%	0.618	42.75%	0.124	36.89%	0.320	37.85%	0.528	20.82%	0.202

** represents statistical significant difference at 5% confident level

* represents statistical significant difference at 10% confident level

Table XI: Correct buy signals

The result present in table are of full 10 years sample period in each size quintiles, ‘emitted’ is number of signals generated by trading strategy, ‘Buy tr’ is number of position taken, ‘correct’ is number of correct signals and ‘(%)’ is percentage of correct signals which is the number of correct signal divided by number of transactions.

	Quintile 1				Quintile 2				Quintile 3				Quintile 4				Quintile 5			
Rules	emited	Buy tr	correct	(%)	emited	Buy tr	correct	(%)	emited	Buy tr	correct	(%)	emited	Buy tr	correct	(%)	emited	Buy tr	correct	(%)
MACD	87	87	37	42.5%	87	87	34	39.1%	80	80	30	37.5%	84	83	32	38.6%	97	97	34	35.1%
1,50,1	23	15	8	53.3%	17	13	4	30.8%	20	15	7	46.7%	24	16	3	18.8%	12	9	5	55.6%
1,100,1	16	11	4	36.4%	18	14	5	35.7%	14	12	6	50.0%	18	10	3	30.0%	13	6	3	50.0%
1,150,1	17	13	4	30.8%	18	13	5	38.5%	11	6	2	33.3%	17	10	2	20.0%	6	5	4	80.0%
1,200,1	15	11	4	36.4%	18	10	2	20.0%	14	12	2	16.7%	13	6	3	50.0%	2	1	1	100.0%
2,50,1	12	9	5	55.6%	16	8	3	37.5%	15	7	3	42.9%	11	9	3	33.3%	5	3	1	33.3%
2,100,1	11	4	3	75.0%	12	10	4	40.0%	7	6	4	66.7%	6	6	2	33.3%	4	3	1	33.3%
2,150,1	7	5	2	40.0%	5	5	1	20.0%	8	5	2	40.0%	7	3	3	100.0%	4	3	2	66.7%
2,200,1	10	7	3	42.9%	6	5	3	60.0%	7	5	3	60.0%	6	6	2	33.3%	3	1	0	0.0%
5,50,1	6	4	3	75.0%	6	4	3	75.0%	6	4	2	50.0%	3	2	2	100.0%	2	1	1	100.0%
5,100,1	4	2	1	50.0%	6	2	0	0.0%	4	2	1	50.0%	5	3	2	66.7%	3	2	1	50.0%
5,150,1	4	1	0	0.0%	4	3	0	0.0%	4	2	1	50.0%	3	2	2	100.0%	1	1	0	0.0%
5,200,1	5	4	1	25.0%	1	1	1	100.0%	4	4	0	0.0%	6	2	0	0.0%	1	1	1	100.0%

Table XII: Correct sell signals

The result present in table are of full 10 years sample period in each size quintiles, ‘emitted’ is number of signals generated by trading strategy, ‘Sell tr’ is number of position taken, ‘correct’ is number of correct signals and ‘(%)’ is percentage of correct signals which is the number of correct signal divided by number of transactions

	Quintile 1				Quintile 2				Quintile 3				Quintile 4				Quintile 5			
Rules	emitted	Sell tr	correct	(%)	emitted	Sell tr	correct	(%)	emitted	Sell tr	correct	(%)	emitted	Sell tr	correct	(%)	emitted	Sell tr	correct	(%)
MACD	88	87	37	42.5%	88	87	32	36.8%	81	80	29	36.3%	84	84	31	36.9%	98	97	32	33.0%
1,50,1	26	16	7	43.8%	26	13	5	38.5%	29	15	7	46.7%	27	16	6	37.5%	15	8	5	62.5%
1,100,1	16	11	6	54.5%	20	13	4	30.8%	22	12	4	33.3%	18	10	4	40.0%	13	7	1	14.3%
1,150,1	15	13	3	23.1%	18	12	3	25.0%	13	7	2	28.6%	14	10	2	20.0%	15	6	1	16.7%
1,200,1	15	10	3	30.0%	18	10	2	20.0%	15	11	2	18.2%	13	7	2	28.6%	7	2	0	0.0%
2,50,1	15	9	5	55.6%	14	9	4	44.4%	15	8	2	25.0%	16	8	5	62.5%	3	3	2	66.7%
2,100,1	5	5	1	20.0%	11	9	3	33.3%	13	6	3	50.0%	10	6	3	50.0%	7	3	1	33.3%
2,150,1	8	6	0	0.0%	12	5	2	40.0%	10	6	2	33.3%	4	4	0	0.0%	4	2	2	100.0%
2,200,1	8	7	1	14.3%	9	5	2	40.0%	9	5	2	40.0%	11	6	3	50.0%	3	1	0	0.0%
5,50,1	6	5	1	20.0%	5	5	3	60.0%	7	4	1	25.0%	5	2	2	100.0%	3	2	1	50.0%
5,100,1	6	3	1	33.3%	4	3	0	0.0%	4	3	0	0.0%	5	3	1	33.3%	2	2	1	50.0%
5,150,1	1	1	0	0.0%	5	2	2	100.0%	5	3	0	0.0%	4	3	1	33.3%	1	1	0	0.0%
5,200,1	4	3	2	66.7%	4	1	1	100.0%	5	3	2	66.7%	2	2	0	0.0%	4	1	1	100.0%