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How Rewarding Is Technical Analysis? Evidence From Singapore Stock Market

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Abstract: This paper focuses on the role of technical analysis in signalling the timing of stock market entry and exit. Test statistics are introduced to test the performance of the most established of the trend followers, the Moving Average, and the most frequently used counter-trend indicator, the Relative Strength Index. Using Singapore data, the results indicate that the indicators can be used to generate significantly positive return. It is found that member firms of Singapore Stock Exchange (SES) tend to enjoy substantial profits by applying technical indicators. This could be the reason why most member firms do have their own trading teams that rely heavily on technical analysis.

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I. INTRODUCTION

Technical analysis involves searching for recurrent and predictable patterns in stock prices. This type of analysis has a long history and dates back to the Japanese rice traders trading on the Dojima Rice Exchange in Osaka as early as the 1600s. It evolved into chartism in the early 20th century with mechanical trading rules to generate signals. This development has since been aided by the introduction of electronics which took the tedium out of complex mathematical manipulations. As computers have become more powerful and their use more widespread, analysts have begun to combine fundamental economic data with the more traditional price and volume data to produce new indicators. More recently, concepts like chaos theory, fuzzy logic, artificial neural network, genetic algorithms, and so on, have been applied to the financial markets. This could well be the next stage of the evolution of technical analysis.

Since the seminal work of Friedman (1953) and Fama (1970), the role of technical analysis as a forecasting mechanism continues to remain controversial in the literature. As will be briefly discussed in the next section, several influential studies conclude that technical analysis is not useful. On the other hand, there is strong evidence that simple forms of technical analysis contain significant forecasting power. In this paper, our objective is to provide new evidence on this issue. Singapore Straits Times Industrial Index (STII) data is used to investigate whether the technical indicators do play any useful role in the timing of stock market entry and exit. More specifically, appropriate test statistics are introduced to test whether the buy and sell signals yield significantly positive return and a test for the difference in returns given by both buy signals and sell signals. The focus is on the most established of the trend followers, the Moving Average (MA), and the most frequently used counter-trend indicator, the Relative Strength Index (RSI). Interestingly, the results indicate that both indicators pass the test in generating significantly positive return. It is found that member firms of Singapore Stock Exchange (SES) tend to enjoy substantial profits by applying technical indicators. This could be the reason why most member firms do have their own trading teams that rely heavily on technical analysis.

The paper is organized as follows. The next section gives a brief review of the existing literature. Section III discusses the simple technical indicators which are widely used in the financial market. In Section IV discusses the data and methodology. Empirical results are contained in Section V, followed by some concluding comments in the final section.

II. A SKELETAL REVIEW OF LITERATURE

The use of market timing has long been the subject of much discussion. Several researchers question the usefulness of such techniques, arguing that such techniques usually cannot produce better returns than a buy-and-hold (B-H) strategy. Many filter rules were tested on the US stock market, with most of them concluding that filter rules do not generate superior returns to the B-H strategy. If the cost of transactions were considered, the returns could even be negative (Fama and Blume 1966; Jensen and Benington 1970). These results are consistent with the efficient markets hypothesis. This hypothesis implies that technical analysis is without merit. In an efficient market, the current price reflects all available information including the past history of prices and trading volume. As investors compete to exploit their common knowledge of a stock's price history, they necessarily drive stock prices to levels where expected rate of return are exactly commensurate with risk. At those levels one cannot expect abnormal returns (see Fama, 1970).

Although technicians recognize the value of information on future economic prospects of the firm, their position is that such information is not mandatory for a successful trading strategy. The reason is that whatever the fundamental reason for a change in the stock price, if the stock price is sluggish to adjust, the analyst should be able to identify a trend that could be exploited during the adjustment period. Consequently, the key to successful technical analysis is a lazy response of stock prices to fundamental supply-and-demand phenomena. Note that this prerequisite is diametrically opposite to the notion of an efficient market.

Practitioners' reliance on technical analysis is well documented. Frankel and Froot (1990a) noted that market professionals tend to include technical analysis in forecasting the market. There is also a shift away from the fundamentals to technical analysis in the 1980s, according to a survey done by Euromoney (see Frankel and Froot, 1990a). On a market level, the prevalence of technical analysis is demonstrated by the fact that most real time financial information services, like Reuters and Telerate, provide detailed, comprehensive and up-to-date technical analysis information. It is obvious that the frequent upgrading of technical analysis services is a response to the demand for technical analysis services and competition among the financial information service providers.

The guiding principle of technical analysis is to identify and go along with the trend. When there is a trend, whether started by random or fundamental factors, technical methods will tend to generate signals in the same direction. This reinforces the original trend, especially when many investors rely on the technical indicators. Thus, even if the original trend were a random occurrence, the subsequent prediction made by the technical indicator could be self-fulfilling. This self-fulfilling nature leads to the formation of speculative bubbles (see, for example, Froot et al., 1992). Conrad and Kaul (1988) found that weekly returns were positively autocorrelated, particularly for portfolios of small stocks. Frankel and Froot (1990b) suggested that the overpricing of the US dollar in the 1980s with respect to the underlying economic fundamentals could be due to the influence of technical analysis. Shiller (1984, 1987) found that irrational investor behaviour resulted in excess bond and stock market volatility. He also suggested that the October 1987 world-wide stock market crash could be due largely to technical analysis. Fama and French (1988) proposed a mean reverting model to explain stock price movements. They also found that autocorrelation of returns become strongly negative for a 3-5 year horizon. DeBondt and Thaler (1985, 1987) found that stocks that were extreme losers over a 3-5 year period tend to have strong returns relative to the market during the following years. Conversely, extreme winners tend to have weaker returns in subsequent years. Sy (1990) had argued against Sharpe's (1975) conclusion, saying that there was no need for the predictive accuracy to be as high as 70 percent for the gains to be large. In addition, he demonstrated that market timing would be increasingly rewarding when the difference in returns between cash and stocks were narrowed and when market volatility increased.

Balvers et al. (1990) show empirically that stock returns could be predicted based on national aggregate output. Other studies have shown that some fundamental data like price earnings ratio, dividend yields, business conditions and economic variables can predict to a large degree the returns on stocks (Campbell, 1987; Campbell and Shiller, 1988a, 1988b; Fama and French, 1989; Breen et al., 1990; among others). For further innovations, see Wong (1993, 1994) and Wong et al. (2001). More recently, Lo et al. (2000) examined the prevalence of various technical patterns in American share prices over 1962-96 and found the patterns to be unusually recurrent. The study does not prove that the patterns are predictable enough to make sufficient profit to justify the risk, but the authors conclude that this is likely.[1]

Despite voluminous literature, the role of technical analysis is far from clearly understood. Technical analysis of some form is a norm in our financial markets, and consequently, the entire subject of active financial management remains intriguing in the context of market efficiency. We need considerably more work to make things more transparent.

III. TECHNICAL INDICATORS

There are several technical indicators in use by practitioners, but generally, they can be classified into two major categories: trend followers and counter-trend indicators. In this section, we discuss briefly the most established of the trend followers, namely, the moving average, and the most frequently used counter-trend indicator, known as the relative strength index.

Moving Averages (MA)

The most widely used moving average (MA) is the n-day simple MA given by:

$$\begin{aligned} M_{t,n} &= \frac{1}{n}\sum_{i=t-n+1}^{t} C_i \\ &= (C_t + C_{t-1} + \cdots + C_{t-n+2} + C_{t-n+1})/n \qquad (1) \end{aligned}$$

where $M_{t,n}$ is the simple n-day moving average at period t and C_i is the closing price for period i. In the simple MA procedure, a buy signal is generated when the closing price rises

[1]The Lo study is cited in 'Economics Focus: Using charts to predict share prices,' The Economist, 19 August 2000, p 78.

above the MA and a sell signal is generated when the close falls below the MA. If there were a clear trend, this method would work well. If, however, the market were moving sideways or if there were excessive volatility, there could be a lot of whipsaws (false signals).

Variants of moving averages include the dual moving average system, the triple moving average system, and the t-ratio on moving averages. The dual moving average is the use of two moving averages while the triple moving average is the use of three moving averages. The t-ratio of moving average is the ratio of simple MA and its standard deviation such that

$$T_{t,n} = \frac{M_{t,n}}{S_{t,n}}$$

where $M_{t,n}$ is the simple moving average defined in (1) and

$$S_{t,n} = \sqrt{\frac{\sum_{i=t-n+1}^{t}(C_i - M_{t,n})^2}{n-1}}\ .$$

Relative Strength Index (RSI)

The calculation of the $RSI_{t,p}$ at time t of period p uses only closing prices and is the ratio of up-closes, U_i, to down-closes, D_i, over the time period selected, expressed as an oscillator that has a range of 0 to 100. The calculation start with defining an index set $I_{t,p} = \{i : t-p \le i \le t\}$, followed by defining the up-closes and the down-closes such that

$$U_i = \begin{cases} C_i - C_{i-1} & if \;\; C_i > C_{i-1} \\ 0 & otherwise \end{cases}$$

$$D_i = \begin{cases} C_{i-1} - C_i & if \;\; C_{i-1} > C_i \\ 0 & otherwise \end{cases}$$

for any $i \in I_{t,p}$ and C_i is the closing price for period i. The next step is to define

$$\begin{aligned} \overline{U}_{t,p} &= Average\,of\;U_i\;over\;I_{t,p} \\ \overline{D}_{t,p} &= Average\,of\;D_i\;over\;I_{t,p} \end{aligned}$$

and thereafter the Relative Strength is given as follows:

$$RS_{t,p} = \frac{\overline{U}_{t,p}}{\overline{D}_{t,p}} \, .$$

The RSI at time t for period p is then defined as:

$$RSI_{t,p} = 100 - \frac{100}{1 + RS_{t,p}} \, . \qquad (2)$$

Readings of 100 imply that there are pure upward price movements, while readings of 0 imply that there are pure downward price movements. Hence a reading close to 100 indicates an overbought market, while a reading around 0 indicates an oversold market. The time period for RSI is found to be shorter for more volatile markets and longer for less volatile markets. Generally, the longer the time period used, the less frequent and more stable are the trading signals. Shorter time periods tend to generate more noise (erratic movements and false signals) than longer periods. For example, using a time period of 14 days, the market tops and bottoms are deemed to occur after the RSI goes above 70 or below 30. Using longer time periods would mean setting less extreme levels for which the market is considered to be overbought or oversold. Thus for a 20-day RSI, the levels may be 60 and 40. Note that the RSI is an oscillator and a counter-trend indicator. If used in a trending market, the RSI often becomes entrenched near one end of the range for days, or even weeks, giving false indications of a market top or bottom.

RSI is used in various forms including 'Touch', 'Peak', 'Retracement' and '50 Crossover' methods. The 'touch' method generates a buy signal when the RSI touches the lower bound (typically set at 30) which indicates that the market is oversold and hence a time to buy. It generates a sell signal when the RSI touches the upper bound (typically set at 70) which indicates that the market is overbought and hence a time to sell. The 'peak' method generates a buy signal when the RSI has crossed the lower bound (typically set at 30) and turned back. It generates a sell signal when the RSI has crossed the upper bound (typically set at 70) and turned back. The 'retracement' method generates a buy signal when the RSI has crossed the lower bound (typically set at 30) and retraced back to the same lower bound or higher. It generates a sell signal when the RSI has crossed the upper bound (typically set at 70) and retraced back to the same upper bound or lower. The '50 crossover' method generates a buy signal when the RSI rises above 50 and a sell signal when the RSI falls below 50.

IV. DATA AND METHODOLOGY

The daily close of the Singapore STII for the period from 1 January 1974 and 31 December 1994 was used, a total of 21 years. As conventional, the full sample is divided into 3 sub-periods of 7 years each. Note that we wanted to avoid the recent period of Asian financial turmoil since 1997, and the original end-point of the data was December 31 1996. For the 7-year sub-period consideration, 1995 and 1996 were dropped with no loss of generality in results. Test statistics were used to test whether the buy and sell signals yield significantly positive return. A test statistic was also introduced for the difference in returns given by the buy and sell signals. Specifically, the following moving averages were tested: 5-day simple MAs, 3-5-day dual MAs, 4-9-18-day triple MA, 5-day t-ratio MA. For RSI, 6-period methods were used for 'touch', 'peak', 'retracement' and 'crossover', but results are reported only for 'crossover' method for reasons discussed later.[2]

The closing prices of the STII were used to compute the daily returns, r_t, from $r_t = ln\,(STII_t/STII_{t-1})$ where $STII_t$ is the closing value of STII for day t. The indicator to be tested provides the buy and sell signals. Then the number of days after the signal to be tested is determined. For example, if the number of days is set to be x, and the buy signal is under tested, the chosen daily returns will be all the daily returns up to x days after the buy signal or up to the next sell signal, whichever is less. Suppose we have buy signals at $t_1, t_2, \cdots, t_m$ and $\Lambda = \{t_1, t_2, \cdots, t_m\}$. Ω is defined to be the set of all these daily returns such that $\Omega = \cup_{t_i \in \Lambda} I_i$ where $\{I_i\}$ are disjoint intervals generated by the i^{th} buy signals at t_i and $n = N(\Omega)$, the number of elements in the set Ω. Note that the length of I_i may be different from I_j for $i \neq j$.

[2] We also tested for 10, 20 and 50-day simple MAs, 3-10, 3-20, 3-50 dual MAs, 10, 20, 50-day t-ratio MA and linear regression analysis with periods 10, 20 and 50. For RSI, we had 14 and 20-period for 'touch', 'peak', 'retracement' and 'crossover' methods. These results are not reported in this paper, but available on request.

The average return, $\bar{r}$, for the period tested, will be :

$$\bar{r} = \frac{\sum_{i\,\epsilon\,\Omega} r_i}{n} \tag{3}$$

where $\bar{r} \sim N(\mu, \sigma^2/n)$. If Ω is the set of all the daily returns generated by buy signals, $\bar{r}_{buy}$ and n_{buy} correspond to $\bar{r}$ and n respectively. Similarly, if Ω is the set of all daily returns generated by sell signals, the symbol $\bar{r}_{sell}$ and n_{sell} are used.

Let μ_{buy} and μ_{sell} be the means of the daily returns generated by buy signals and sell signals respectively and let σ_{buy} and σ_{sell} be the standard deviation of the daily returns generated by buy signals and sell signals respectively. Since it is expected that the returns will be positive for the buy signal, we test the hypothesis $H_{01} : \mu_{buy} = 0 \;\; vs \;\; H_{11} : \mu_{buy} > 0$ using the test statistic:

$$T_b = \frac{\bar{r}_{buy}}{s/\sqrt{n_{buy}}} \;.$$

Without loss of generality, it is assumed the standard deviations of the daily returns are the same for those generated by buy signals and by sell signals. As such, the pooled estimator s is used to estimate both σ_{buy} and σ_{sell} where s is the standard error estimated for the daily return from the entire sample. In this situation, $T_b \sim N(0, 1)$ if H_{01} is true. Hence, for an α level of significance, if $T_b > z_\alpha$, we will reject $H_{01} : \mu_{buy} = 0$ and conclude that the return is significantly larger than zero. The statistic T_b is presented in the tables as Stat-B.

Similarly, the test statistic $T_s = \bar{r}_{sell}/(s/\sqrt{n_{sell}})$ is used to test the hypothesis $H_{02} : \mu_{sell} = 0 \;\; vs \;\; H_{12} : \mu_{sell} < 0$ since the returns are expected to be negative for the sell signal. If the test statistic, $T_s < -z_\alpha$, the null hypothesis H_{02} is rejected and it can be concluded that the returns are significantly smaller than zero. The statistic T_s is presented in the tables as Stat-S.

The buy signal is expected to be positive and the sell signal negative, the difference, $\bar{r}_D = \bar{r}_{buy} - \bar{r}_{sell}$ will be positive. In order to study the joint effect of buy and sell signals, the hypothesis $H_{03} : \mu_D = 0 \;\; vs \;\; H_{13} : \mu_D > 0$ is also tested using the test statistic $T_D = (\bar{r}_D - 0)/[s\,(1/\sqrt{n_{buy}} + 1/\sqrt{n_{sell}})]$. If $T_D > z_\alpha$, the null hypothesis H_{03} is rejected and it can be concluded that the difference in returns is significantly larger than zero. The statistic T_D is presented in the tables as Stat-BS.

A summary of the above is given in Table 1. In this table, statistics that are significant at the 1% level are marked ‘a’, those significant between 1% to 5% level are marked ‘b’, the ones significant between 5% to 10% level and are marked ‘c’. For statistics that are of the incorrect sign, the markings are ‘d’, ‘e’ and ‘f’ for 1%, between 1% to 5%, and between 5% to 10%, respectively. The range of values for the buy, sell and the difference between buy and sell are given in Table 1.

Table 1. Summary scheme of tests

Significant level	Stat-B and Stat-BS	Stat-S	Markings
1%	$T > 2.3263$	$T < -2.3263$	a
1% to 5%	$2.3263 > T > 1.6449$	$-2.3263 < T < -1.6449$	b
5% to 10%	$1.6449 > T > 1.2816$	$-1.6449 < T < -1.2816$	c
1%	$T < -2.3263$	$T > 2.3263$	d
1% to 5%	$-2.3263 < T < -1.6449$	$2.3263 > T > 1.6449$	e
5% to 10%	$-1.6449 < T < -1.2816$	$1.6449 > T > 1.2816$	f

Note : see text for definitions.

V. RESULTS

As described in Section IV, the entire period is divided into three sub-periods of 7 years each. These sub-periods are shown as ‘Per 1’, ‘Per 2’ and ‘Per 3’ in the tables. The result for the entire sample is given by the row marked ‘Whole’. The number of days after the signal to be tested is given by the column under ‘Day’. Here, the mean for the buy signal is denoted by ‘Mean-B’ and that for the sell signal denoted by ‘Mean-S’. The test statistics for the buy signal, the sell signal and the difference between the buy and the sell signals are denoted as ‘Stat-B’, ‘Stat-S’ and ‘Stat-BS’ respectively.

Single moving average

Table 2 gives the results for the single 5-day moving average. As can be seen in the table,

Table 2. Single 5-day moving average

Period	Day	Mean-B	Mean-S	Stat-B	Stat-S	Stat-BS
Per 1	5	0.00303	-0.00133	1.93603b	-0.81338	1.92569b
Per 2	5	0.00320	-0.00267	2.14885b	-1.77323b	2.77186a
Per 3	5	0.00258	-0.00054	1.78564b	-0.35542	1.48770c
Whole	5	0.00293	-0.00153	3.38493a	-1.70839b	3.57999a
Per 1	10	0.00282	-0.00150	2.15596b	-1.05753	2.23846b
Per 2	10	0.00282	-0.00283	2.18656b	-2.15836b	3.07202a
Per 3	10	0.00175	-0.00110	1.41118c	-0.80681	1.54768c
Whole	10	0.00244	-0.00184	3.30826a	-2.34555a	3.97456a
Per 1	20	0.00280	-0.00180	2.27973b	-1.36669c	2.55366a
Per 2	20	0.00267	-0.00264	2.16233b	-2.07289b	2.99343a
Per 3	20	0.00179	-0.00095	1.49065c	-0.72146	1.53783c
Whole	20	0.00241	-0.00182	3.41876a	-2.41586a	4.10076a
Per 1	30	0.00275	-0.00189	2.24594b	-1.46217c	2.60609a
Per 2	30	0.00267	-0.00264	2.17395b	-2.07289b	3.00121a
Per 3	30	0.00184	-0.00095	1.54385c	-0.72146	1.57075c
Whole	30	0.00241	-0.00185	3.43596a	-2.47085a	4.15307a

See text for definitions.

all Mean-B are positive and all Mean-S are negative. This shows that both buy signals and sell signals generate positive return, on average. All the test statistics were of the correct sign. Moreover, all the statistics for the buy signal were significant at the 10% level or better. The statistics for period 1 and period 2 were always significant at the 5% level while that for period 3 were mostly significant at the 10% level. The statistics for the whole period were significant at the 1% level.

For the sell signal, the statistics for period 2 were consistently significant at the 5% level. For period 1, the results became significant only when the number of days tested was 20 or larger. For the whole period, the results were significant at the 1% level when 10 or more days were included in the test. For the difference between the buy and sell signals, all the results were significant, with the results becoming progressively better as the number of days included in the test increased.[3]

Dual Moving Average

Table 3 gives the results for the dual 3-day, 5-day moving average. As can be seen, most of the test statistics were of the correct sign, with the exception of the statistics for the 5 day sell signal in period 3.

Table 3. Dual moving average (3-day, 5-day)

Period	Day	Mean-B	Mean-S	Stat-B	Stat-S	Stat-BS
Per 1	5	0.00229	-0.00023	1.46805c	-0.13957	1.11813
Per 2	5	0.00164	-0.00156	1.08981	-1.02330	1.49389c
Per 3	5	0.00171	0.00007	1.16835	0.04817	0.77455
Whole	5	0.00187	-0.00059	2.14476b	-0.65270	1.96192b
Per 1	10	0.00219	-0.00064	1.68754b	-0.45259	1.47499c
Per 2	10	0.00153	-0.00163	1.18547	-1.23186	1.70958b
Per 3	10	0.00121	-0.00039	0.95792	-0.28436	0.85998
Whole	10	0.00163	-0.00090	2.20619b	-1.14986	2.34945a
Per 1	20	0.00199	-0.00104	1.64137c	-0.78350	1.68640b
Per 2	20	0.00151	-0.00141	1.23036	-1.10500	1.64926b
Per 3	20	0.00126	-0.00027	1.04794	-0.20258	0.85843
Whole	20	0.00159	-0.00091	2.26297b	-1.21321	2.43043a
Per 1	30	0.00194	-0.00112	1.61202c	-0.85508	1.72210b
Per 2	30	0.00151	-0.00141	1.23477	-1.10500	1.65227b
Per 3	30	0.00129	-0.00027	1.07594	-0.20258	0.87512
Whole	30	0.00158	-0.00094	2.26452b	-1.25500	2.46221a

See text for definitions.

All Mean-B are positive and all Mean-S (except for period 3 with a 5-day test period) are negative. These indicate that both buy signals and sell signals generate positive return, on average. All the test statistics (except Stat-S for period 3 with 5-day test period) were of the correct sign. Moreover, for the buy signal, all the statistics for period 1 were significant at the 10% level, and for the whole period, they were significant at the 5% level. For the sell signal, none of the statistics were significant.

[3]For 10, 20 and 50-day simple moving average, the results were even better. Generally the results became progressively better as the number of days being tested increased. The results were also better for shorter durations of the moving average.

For the difference between the buy and sell signals, most of the results for period 1 were significant, except when the number of days included in the test was 5. For period 2, all the results were significant with the level of significance increasing with the number of days tested. For the whole period, all the results were significant with the level of significance increasing from the 5% level to the 1% level as the number of days tested increased. Overall, the results for the buy signal as well as for the difference between the buy and sell signals were reasonably good for the chartists.[4]

Triple moving average

Table 4 gives the results for the triple moving average. Following market practitioners, 4-day, 9-day and 18-day moving averages were used. It can be seen that most of the test statistics were of the correct sign, the main exception being the statistics for the sell signal in period 3. For the buy signal, the statistics for period 1 were significant at the 10% level when the number of days tested was 20 or larger. For the whole period, all the statistics were significant. For the sell signal, none of the statistics were significant, although most of them were of the correct sign. For the difference between the buy and sell signals, most of the results for period 1 were significant, except when the number of days included in the test was 5 or 10. For period 2, all the results were significant at the 10% level of significance. For the whole period, most of the results were significant, except when the number of days tested was 5. Overall, the results for the buy signal as well as for the difference between the buy and sell signals were quite good, and quite a number of the statistics were significant.

t-ratio on moving average

Table 5 gives the results for the t-ratio on the 5-day moving average. As can be seen, all the test statistics for the buy signal as well as for the difference between buy and sell signals

[4]For 3-10, 3-20, 3-50 dual moving average, nearly all test statistics were of the correct sign. Overall, the results for the buy signal as well as for the difference between the buy and sell signals were quite impressive. Note that the results for buy signal were better for shorter periods while those for the sell signal were better for longer periods. With the difference between the buy and sell signals, the results were slightly better for shorter periods.

Table 4. Triple moving average (4-day, 9-day, 18-day)

Period	Day	Mean-B	Mean-S	Stat-B	Stat-S	Stat-BS
Per 1	5	0.00228	-0.00075	0.99648	-0.30577	0.90474
Per 2	5	0.00225	-0.00215	0.99019	-0.98088	1.39364c
Per 3	5	0.00098	0.00128	0.48370	0.62684	-0.10541
Whole	5	0.00177	-0.00043	1.39976c	-0.33940	1.22574
Per 1	10	0.00181	-0.00060	1.03551	-0.31378	0.92951
Per 2	10	0.00198	-0.00118	1.11109	-0.70619	1.29372c
Per 3	10	0.00052	0.00011	0.31779	0.06743	0.17821
Whole	10	0.00138	-0.00054	1.39651c	-0.54022	1.36882c
Per 1	20	0.00195	-0.00078	1.32653c	-0.51137	1.28865c
Per 2	20	0.00194	-0.00102	1.27645	-0.76765	1.46601c
Per 3	20	0.00066	0.00012	0.45834	0.09304	0.27919
Whole	20	0.00150	-0.00053	1.75633b	-0.66589	1.73965b
Per 1	30	0.00208	-0.00083	1.48498c	-0.60188	1.47896c
Per 2	30	0.00166	-0.00078	1.15626	-0.64130	1.29666c
Per 3	30	0.00079	0.00047	0.56484	0.39358	0.17277
Whole	30	0.00151	-0.00033	1.84851	-0.45896	1.68485b

See text for definitions.

were of the correct sign. For the buy signal, all the statistics for period 1 and the whole period were significant. However, for the sell signal, none of the statistics were significant, although most of them were of the correct sign. For the difference between buy and sell signals, most of the results for period 1 were significant, except when the number of days included in the test was 5. For period 2, the results when the number of days tested was 20 were significant at the 10% level. For the whole period, most of the results were significant, except when the number of days included in the test was 5.[5]

Relative strength index (RSI)

For RSI, results are reported using the '50 crossover' method only. Note that routines were run using 'touch', 'peak' and 'retracement' methods. Unfortunately, the empirical results for these procedures were mixed. Hence, for brevity, these results are not included here

[5]For 10, 20, 50-day t-ratio moving average, all the test statistics were of the correct sign. Overall, the results for the buy signal as well as for the difference between buy and sell signals were quite good, with quite a number of the results significant.

Table 5. t-Ratio on moving average (5-day MA, sample size 3)

Period	Day	Mean-B	Mean-S	Stat-B	Stat-S	Stat-BS
Per 1	5	0.00264	0.00054	1.46257c	0.33290	0.86095
Per 2	5	0.00184	-0.00062	1.06724	-0.40399	1.06696
Per 3	5	0.00139	0.00124	0.81384	0.80846	0.06455
Whole	5	0.00193	0.00038	1.91935b	0.42051	1.14877
Per 1	10	0.00264	-0.00010	1.73090b	-0.07431	1.34521c
Per 2	10	0.00168	-0.00079	1.09606	-0.63065	1.24833
Per 3	10	0.00098	0.00061	0.64254	0.47706	0.19009
Whole	10	0.00177	-0.00010	2.00457b	-0.13786	1.62294c
Per 1	20	0.00244	-0.00046	1.67302b	-0.39195	1.54630c
Per 2	20	0.00163	-0.00083	1.08084	-0.74647	1.31286c
Per 3	20	0.00118	0.00028	0.78948	0.24651	0.47973
Whole	20	0.00176	-0.00034	2.05197b	-0.51611	1.94122b
Per 1	30	0.00244	-0.00063	1.67302b	-0.55706	1.66363b
Per 2	30	0.00163	-0.00070	1.08084	-0.64140	1.25142
Per 3	30	0.00122	0.00021	0.83058	0.18773	0.55125
Whole	30	0.00177	-0.00037	2.07322b	-0.58259	2.00779b

See text for definitions.

(but available on request).

Table 6 gives the results for a six-period relative strength index using the '50 Crossover' method. As can be seen, all the test statistics were of the correct sign. For the buy signal, the statistics for period 1 were significant at the 5% level when the number of days tested was 20 or greater. For period 2, the statistics were significant when the number of days tested was 10 or greater. For the whole period, all the statistics were significant at the 5% or 1% level. For the sell signal, all the statistics for period 2 were significant at the 5% level. For the whole period, all the statistics were significant, mostly at the 5% level. For the difference between **the** buy and sell signals, all the results for period 1 were significant. For period 2, all the results were significant, mostly at the 1% level. For the whole period, all the results were significant at the 1% level. Overall, the results were very impressive, and the majority of the statistics were significant.[6]

[6]For 14 and 20-period with 'crossover' methods, all the test statistics were of the correct sign. Overall, the results were very impressive, and the majority of the statistics were significant.

Table 6. Six-period RSI using the '50 crossover' method

Period	Day	Mean-B	Mean-S	Stat-B	Stat-S	Stat-BS
Per 1	5	0.00233	-0.00150	1.11462	-0.72489	1.30225c
Per 2	5	0.00245	-0.00328	1.24421	-1.75141b	2.10825b
Per 3	5	0.00203	-0.00055	1.14038	-0.29936	1.01051
Whole	5	0.00225	-0.00177	2.01573b	-1.60158c	2.55938a
Per 1	10	0.00190	-0.00145	1.14553	-0.84852	1.40677c
Per 2	10	0.00221	-0.00309	1.39370c	-2.02021b	2.40591a
Per 3	10	0.00148	-0.00074	1.04016	-0.48694	1.06551
Whole	10	0.00184	-0.00178	2.05387b	-1.95154b	2.83124a
Per 1	20	0.00228	-0.00158	1.66565b	-1.06075	1.90828b
Per 2	20	0.00243	-0.00254	1.80313b	-1.87950b	2.60403a
Per 3	20	0.00148	-0.00049	1.21398	-0.35131	1.06239
Whole	20	0.00202	-0.00156	2.67816a	-1.91598b	3.22600a
Per 1	30	0.00230	-0.00152	1.83674b	-1.07979	2.02752b
Per 2	30	0.00238	-0.00230	1.90023b	-1.77368b	2.59587a
Per 3	30	0.00129	-0.00045	1.10894	-0.32025	0.95612
Whole	30	0.00195	-0.00147	2.77393a	-1.86158b	3.23698a

See text for definitions.

As mentioned earlier, the Relative Strength Index using the 'touch', 'peak' and 'retracement' methods all produce mixed results. This is probably due to the fact that the RSI is good when used in a non-trending environment, but indiscriminate use of this indicator often leads to dismal results. Furthermore, it is argued that RSI should be used when another indicator called the Average Directional Movement Index (ADX) shows the market to be non-trending.[7] Since the daily high and low prices that are required to compute the ADX were not available, the RSI have been applied to the entire region. This poses some problems since the market is often trending. However, the results reported in this study provide evidence that technical indicators can play a useful role in the timing of stock market entry and exits.

[7]e.g. see LeBeau and Lucas (1992).

VI. CONCLUSION

The results indicate that in general, single moving averages produce the best results, followed by the dual moving average and the relative strength index using the '50 crossover' method. Note that transaction costs are not included in this paper. In Singapore, the main transaction cost is the commission. The commission rate varies according to the type of market player involved. Retail investors pay a flat rate of 1%. Large institutional investors such as mutual funds pay around 0.5% or less, depending on the size of the institution. Broking firms with seats in the Stock Exchange of Singapore (SES) effectively do not have to pay any commission, although they do have to pay out a considerable sum to buy the seat. Then again the cost of the seat is a fixed cost and therefore there is effectively no variable cost involved for member firms of the SES. Consequently, the results are applicable more to members of the Stock Exchange of Singapore who effectively do not have to pay any commission.

In general, one can conclude from the results that technical indicators can play a useful role in the timing of stock market entry and exits. By applying technical indicators, member firms of the SES may enjoy substantial profits. It is thus not surprising that most member firms do have their own trading team that rely heavily on technical analysis.

Note that these tests are based on a normality assumption invoking the law of large number. When the test sample size is small, the normality assumption may not be valid. In this situation, one can use the three-moment or four-moment approximation to the test (Tiku and Wong 1998), or use the Modified Maximum Likelihood Estimator approach to modify the test (Tiku, et al. 1999a,b, 2000). Another alternative is to use the robust Bayesian sampling estimators (Matsumura et al 1990; Wong and Bian 2000) to improve the results. One can also use a 'distribution-free' approach to improve the test (Wong and Miller, 1990). Another extension to the test is to include the work of Li and Wong (1999) and Wong and Li (1999) which study the behavior of risk takers and risk averters in the stock market.

REFERENCES

Balvers, R. J., T.F. Cosimano, and B. McDonald, 1990, Predicting Stock Returns in an Efficient Market, *Journal of Finance,* 55, 1109-28.

Breen, W., L.R. Glosten and R. Jagannathan, 1990, Predictable Variations in Stock Index Returns, *Journal of Finance,* 44, 1177-89.

Campbell, J.Y., 1987, Stock Returns and Term Structure, *Journal of Financial Economics,* 18, 373-99.

Campbell, J.Y. and R.J. Shiller, 1988a, The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors, *Review of Financial Studies,* 1, 195-228.

Campbell, J.Y. and R.J. Shiller, 1988b, Stock Prices, Earnings and Expected Dividends, *Journal of Finance,* 43, 661-76.

Conrad, J. and G. Kaul, 1988, Time-Variation in Expected Returns, *Journal of Business,* 61, 409-425.

DeBondt, F.M. Werner and R.H. Thaler, 1985, Does the Stock Market overreact, *Journal of Finance,* 40, 793-805.

DeBondt, F.M. Werner and R.H. Thaler, 1987, Further Evidence on Investor Overreaction and Market Seasonality, *Journal of Finance,* 42, 557-581.

Fama, E.F., 1970, Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance,* 25, May, 383-417.

Fama, E.F. and M. Blume, 1966, Filter Rules and Stock Market Trading Profits, *Journal of Business,* 39 , Special Supplement, January, 226-241.

Fama, E.F. and K. French, 1988, Permanent and Temporary Components of Stock Prices, *Journal of Political Economy,* 96, 246-273.

Fama, E.F. and K. French, 1989, Business Conditions and Expected Returns on Stocks and Bonds, *Journal of Financial Economics,* 25, 23-49.

Frankel, J. and K. Froot, 1990a, The Rationality of the Foreign Exchange Rate: Chartists, Fundamentalists, and Trading in the Foreign Exchange Rate, *American Economic Review,* 80, May, 181-85.

Frankel, J. and K. Froot, 1990b, Chartists, Fundamentalists and the Demand for Dollars, in *Private Behaviour and Government Policy in Interdependent Economies,* A.S. Courakis and M.P. Taylor (eds), Oxford University Press.

Friedman, M., 1953, The Case for Flexible Exchange Rate, in Essays in Positive Economics, Chicago, University of Chicago Press.

Froot, K.A., D.S. Scharfstein and J.C. Stein, 1992. Heard on the street : information inefficiencies in a market with short-term speculators. *Journal of Finance* 47:1461-1484.

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

LeBeau, C. and D.W. Lucas, 1992, *Technical Traders Guide to Computer Analysis of the Futures Market,* Business One Irwin, Richard D. Irwin, Inc.

Li, C.K. and W.K. Wong, 1999, A Note on Stochastic Dominance for Risk Averters and Risk Takers, *RAIRO Recherche Opérationnelle,* 33, 509-524.

Lo, A.W., Mamaysky H. and Wang, J. 2000. Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation. *Journal of Finance,* 55: 1705-1764.

Matsumura, E.M., K.W. Tsui and W.K. Wong, 1990, An Extended Multinomial-Dirichlet Model for Error Bounds for Dollar-Unit Sampling, *Contemporary Accounting Research,* V6, No 2-I, 485-500.

Sharpe, W.F., 1975, Likely Gains From Market Timing, *Financial Analysts Journal,* March-April, 60-69.

Shiller, R.J., 1984, Stock Prices and Social Dynamics, *Brookings Papers on Economic Activity,* 2, Brookings Institution, 71-87.

Shiller, R.J., 1987, Investor Behaviour in the October 1987 Stock Market Crash: Survey Evidence, *NBER Working Paper,* No. 2446. Reprinted in *Market Volatility,* MIT Press.

Sy W., 1990, Market Timing: Is It a Folly? *Journal of Portfolio Management,* 16, Summer, 11-16.

Tiku, M.L. and W.K. Wong, 1998, Testing for Unit Root in AR(1) Model Using Three and Four Moment Approximations, *Communications in Statistics: Simulation and Computation,* 27:185-198.

Tiku, M.L., W.K. Wong and G. Bian, 1999a, Estimating Parameters in Autoregressive Models in Non-normal Situations: symmetric Innovations, *Communications in Statistics: Theory and Methods,* 28:315-341.

Tiku, M.L., W.K. Wong and G. Bian, 1999b, "Time series models with asymmetric innovations," *Communications in Statistics: Theory and Methods,* 28, 1331-1360.

Tiku, M.L., W.K. Wong, D.C. Vaughan and G. Bian, 2000, Time series models with nonnormal innovations: symmetric location–scale distributions, *Journal of Time Series Analysis ,* 21:571-596.

Wong, W.K., 1993, An Equity Indicator for the Singapore Market, *Journal of Singapore Stock Exchange,* May, 21-23.

Wong, W.K., 1994, A Composite Equity Indicator for Singapore, *Journal of Singapore Stock Exchange,* May, 24-26.

Wong, W K and G. Bian, 2000, Robust Bayesian Inference in Asset Pricing Estimation, *Journal of Applied Mathematics & Decision Sciences,* 4:65-82.

Wong W.K., B.K. Chew and D. Sikorski, 2001, Can the Forecasts Generated from E/P Ratio and Bond Yield be Used to Beat Stock Markets? *Multinational Finance Journal,* 5, 59-86.

Wong, W.K. and C.K. Li, 1999, A note on convex stochastic dominance theory, *Economics Letters,* 62, 293-300.

Wong, W.K. and R.B. Miller, 1990, Analysis of ARIMA-Noise Models with Repeated Time Series, *Journal of Business and Economic Statistics,* 8, 243-250.