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TRADING STRATEGIES IN THE CHINESE STOCK MARKET

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Resumo

A análise técnica é um dos principais métodos de previsão e estratégias de negociação nos mercados de valores. Nos últimos 20 anos, a estratégia de momentum tornou-se uma parte importante na investigação de finanças comportamentais. No presente estudo, modelos de negociação com base em 1 indicador e em 2 indicadores foram estabelecidos com a ajuda de Médias Móveis (MA) e do Índice de Força Relativa (RSI), bem como das suas combinações e regras técnicas. Os dois índices bolsistas chineses, nomeadamente o Índice Composto SSE e o Índice Composto SZSE são selecionados como dados do estudo. Depois de configurar sinais de alta e baixa, eu implemento testes para examinar se os retornos médios dos sinais são significativamente diferentes do retorno médio diário, e se o retorno médio de compra é significativamente diferente do retorno médio de venda, para verificar o seu poder preditivo no mercado acionista chinês. Por fim, construo a estratégia de negociação com base em regras de negociação para superar a estratégia de compra e manutenção (buy and hold). Os resultados mostram que a maioria das regras de negociação de MA e RSI são potenciais preditores da evolução futura do mercado, sendo os indicadores mais preditivos a RSI3, a MA20 e a combinação de RSI3 e MA20.

Classificações JEL: C22, G15

Palavras-chave: MA, RSI, estratégias de negociação, mercado acionista chinês.

Abstract

Technical analysis is one of the main forecasting methods and trading strategies in the stock market. In the last 20 years, momentum strategy has become a great concern of behavioral finance. In this study, I establish 1-indicator and 2-indicators trading model, using the Moving Average (MA), the Relative Strength Index (RSI), as well as their combinations as technical rules. Two Chinese stock indices, SSE Composite Index and SZSE Component Index are selected as data. After setting up bullish and bearish signals, I implement t-tests to examine whether the mean returns on signals are significantly different from the mean daily return, and whether the mean buy return are significantly different from the mean sell return, and then check their predictive power in the Chinese stock market. At last, I build the trading strategy based on these predictable trading rules to outperform the buy-and-hold strategy. Results show that most MA and RSI trading rules are potential predictable indicators, with the best predictive indicators being RSI3, MA20 and the combination of RSI3&MA20.

JEL Classification: C22, G15

Key Words: MA, RSI, Trading strategies, Chinese stock market.

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Acronyms

AF	Alexander Filter Rules
B&H	Buy-and-hold
CNY	Chinese Yuan currency
CSR	Candlestick Rules
DJIA	Dow Jones Industrial Average
DJTA	Dow Jones Transportation Average
EMA	Exponential Moving Average
EMH	Efficient Market Hypothesis
EPS	Earning per share
GARP	Growth at a reasonable price
KDJ	KDJ Stochastic Oscillator
MA	Moving Average
MACD	Moving Average Convergence Divergence
PPR	Price Pattern Rules
P/BV	Price-to-book value
P/E	Price-to-earning
RC	White's Reality Check
RSI	Relative Strength Index
RS	Relative Strength
SD	Standard deviations
SPA	Superior Predictive Ability
SSE	Shanghai Stock Exchange
SZSE	Shenzhen Stock Exchange
TRB	Trading Range Break

1. Introduction

In the whole world, if the economy goes through regular cycles and is mirrored by stock prices, then it seems that stock prices go through predictable cycles as well (Smith, 1989). This means that investors need to know where the current economic cycle is going to.

The Chinese market for securities trading has been functioning since the 1860s, in Shanghai. However, the Chinese stock market began its development only in the early 1990s. There are two stock exchanges in the mainland of China, Shanghai Stock Exchange (SSE hereafter) and Shenzhen Stock Exchange (SZSE hereafter), which were funded in 1990. By 2000, the Chinese stock market had over 1000 listed companies.

Almost 80% of investors on the Chinese stock are individuals, or retail investors. Because of their speculative behaviors on overheated markets, an instability performance has been witnessed in the Chinese stock market. Other two common volatility factors of Chinese stock prices are: Chinese government policy and the linkage effects of stocks.

Over the last 20 years there were two stock market turbulences in the Chinese market. The first is the Chinese stock market plunge of 2007, due to the stock market bubble, which resulted in the global market tumble. The second is the stock financing in June 2015, which in January 2016 resulted in the sell-off on the Chinese stock market, hitting stocks in Europe and the United States.

Investors could be of several types, such as technical traders, noise traders, fundamental investors and so on (Wang and Sun, 2015). Insiders and institutional investors want to receive relevant information before individual investors (Smith and Eiteman, 1974). The technical trading strategy described in this dissertation aims to be beneficial, not only for financial professionals and market makers, but also for Chinese individual technical traders.

Several financial institutions or trading teams use both technical analysis and fundamental analysis when investing in securities. Fundamental analysis is a method to evaluate securities using the firm fundamentals, i.e. its underlying characteristics (such as firm size, earnings, value and growth), namely those which are correlated with future returns.

Compared to fundamental analysis, technical analysis is another important and useful method, based on the market historical data for forecasting the future market prices of securities. This technique tries to recognize formations and patterns with historical significance, allowing technical analysts to forecast the future prices just by analyzing their past performance. With such analysis, investors could subsequently implement and identity appropriate buy or sell signals (Smith and Eiteman, 1974).

This dissertation uses technical analysis to identify useful strategies in the Shanghai and Shenzhen stock markets to investors in China. The objective of the study is to evaluate stock's prices with the technical analysis and forecasting methods, as well as to detect potential short-term and long-term trade opportunities for investors. In my study, t-tests results show that most MA and RSI trading rules could potentially predict Chinese stock market, however, it is not observed with RSI9 and RSI14 rules. RSI3, MA20, combination of RSI3&MA20 are the best predictive indicators.

2. Literature review

2.1. Main references and analytical techniques

2.1.1. Technical analysis

Assets and liabilities of firms could be reported in different ways. In consequence, it may be difficult for fundamental analysts to compare several firms' financial statements in different industries and in different countries. In turn, technical analysis is not heavily dependent on financial statements or on other information sources about how a firm or industry has been performing in the past.

Moreover, fundamental analysis evaluates the company's financial statements to determine expected future returns and risk characteristics. As a result, a fundamental analyst must process the new information very quickly and correctly, and then update the forecast to its latest value. On the contrary, technical analysts need only recognize a price movement easily to calculate the new foreseen equilibrium value (Reilly, 1989).

Nevertheless, there are some main disadvantages of technical analysis. First, the majority of studies tend to support that technical analysis is suitable for markets which are inefficient in the weak form. Second, the patterns of evolution of past prices may not be the same in the future. If technical analysts follow previous trading trends and behavior, they may commit mistakes and miss later market turns. However, if they change their investment decisions over time to conform to the new environment, the use of various techniques and timely market judgments could not be completely standard (Reilly, 1989). At last, the success of trading and technical indicators will encourage other investors to use technical analysis, which means sharing high returns with competition, thus reducing their potential investment value (Reilly, 1989).

2.1.2. Dow Theory

Charles Henry Dow, a founding member of the Dow-Jones Company in 1880 as a financial-news service, established *The Wall Street Journal* in 1889, and wrote a series of influential editorials about the stock markets. After Dow's death in 1902, William Peter Hamilton, a disciple of Dow and an editor of *The Wall Street Journal*, interpreted the editorials of Dow's theories until his death in 1929. The Dow Theory has become the basis of technical analysis, supporting technical trading strategies.

The Dow Theory, which follows the momentum strategy, aims to identify long-term trends in stock market prices. It shows that stock markets have three main trends: primary trend, intermediate trends, and minor trends. The first appears on long-term movement of prices, lasting from several months to several years. The intermediate (or secondary) trend reflects short-term deviations of prices from the underlying trend line, eliminated by corrections. Lastly, minor (or tertiary) trends depict daily fluctuations of little importance (Bodie, Kane and Marcus, 2014).

According to the Dow Theory, every bull market eventually turns into a bear market, which then inevitably turns bullish once again (Smith, 1989). A major market would not go straight up (or down), but rather includes small price declines (or increases), so investors decide to take profits from temporary setbacks and reversals (Reilly and Brown, 2006). Cowles (1933) tested the Dow Theory and provided strong evidence of forecasting stock market. More recently, Brown, Goetzmann, and Kumar (1998) formulated an event study to test the ability of the Dow Theory.

Two relative indicators were created with Dow's mark: Dow Jones Industrial Average (DJIA hereafter) and Dow Jones Transportation Average (DJTA hereafter) (Bodie, Kane, Marcus, 1992). DJIA and DJTA reflect production and the transportation average monitors commerce, with increases in both indexes revealing collective analysts and investors acting (Smith, 1989).

2.2. Types of strategies and analysis

2.2.1. Investing strategies

Value investing, established by Graham and Dodd (1934), and growth investing, e.g. Growth at a reasonable price, or 'GARP', popularized by Peter Lynch (1989) are two main traditional trading strategies of fundamental analysis. Investors from value investing, choose underpriced securities depending on high dividend yields, low P/E (price-to-earning), or low P/BV (price-to-book value). People who prefer growth investing, select relative indicators, such as low market cap, high growth in EPS (earning per share), or high P/E.

However, contrarian strategy and momentum strategy, which belong to behavioral finance, have been having a great concern in financial area during the last 20 years. The contrarian strategy, raised by De Bondt and Thaler (1985), focus on buying low price stocks when markets are depressed. It could be compatible with short selling, or market timing strategy following.

The momentum strategy, proposed by Jegadeesh and Titman (1993), is based on assuming that recent stock prices increases lead to further increases, and falling prices stimulate prices to continue falling (Shi, Jiang, Zhou, 2015). They suggested that investors should follow trends, for instance, buy today's winners with bullish trend and sell today's losers with bearish trend. Relative Strength (RS hereafter) is included in the momentum factor. The size factor is one of the three factors of Fama-French (1992, 1993) Model. In 1997, momentum effect was added in Fama-French Model by Carhart, to expand as Four-Factor Model.

2.2.2. Analysis tool

Different technical analysts founded different technical theories. Charts of stock prices trends, which are learnt from the Dow Theory, are commonly utilized by technicians as their primary analysis tool (Smith, 1989). Three kinds of traditional charts are listed as follows: line charting, bar charting, point-and-figure charting (Cohen, Zinbarg, and Zeikel, 1987). Another type of chart, older and powerful, is the Japanese Candlestick Chart, which draws continuous stock price movement with whole day's trading range. Its top is the highest price, and its bottom is the lowest price.

The most popular method is bar charting, which includes the price range and closing price, and even trading volume of the stock during each interval over time (Smith and Eiteman, 1974). Technicians could identify various signals of price movements in a definite upward or downward direction, through the support level or resistance level, which is a barrier to subsequent price decline or advance.

The second one is line charting, connecting the closing prices of successive time periods by straight lines (Cohen, Zinbarg, and Zeikel, 1987). Horizontal axis of both bar charts and line charts represent time, the interval may be a day, a week, a month, a year, or even longer. These charts give short-run forecasting with daily data and a long-run perspective using weekly or monthly data.

The third method is point-and-figure charting, which is focused on significant prices upward and downward trends over time. It uses 'X' to represent a price rise of $1, and 'O' to represent a price decline of $1.

2.3. Investors irrationality

An important characteristic of irrationality, loss aversion, is that investors are unwilling to admit mistakes after investment in behavioral finance. This shortcoming is consistent with efficient market anomalies, such as historical bubbles.

Disposition effect is a behavioral tendency of investors to hold on to losers too long, and to sell winners too quickly. It leads to momentum in stock prices, for instance, winning stocks continue to go up for months after being sold (Shefrin and Statman, 1985), which may cause systematic stocks mispricing. Examining more than 10000 trades at a discount brokerage house, Terrance Odean (1998) supported disposition effect that behavioral investors might be reluctant to realize losses, as they realized only 9.8% of losses, but 14.8% of gains per year.

However, correction will occur when stock have good earnings reports or high returns, so traders could take profits from them. Firstly, excellent performance leads investors to revise their extremely assessments of future. Secondly, buying pressure would be created and prices grow sharply. For example, stocks fall suddenly in their good earnings announcements days. Finally, the difference between market price and intrinsic value becomes smaller, until market corrects its initial error.

2.4. Technical indicators

Nowadays many mathematical methods and professional software are used for technical forecasting stock data, such as technical indicators of the stock charts. The stock price charts demonstrate market peaks and troughs along with rising and declining trends (Reilly and Brown, 2006). Technical indicators predict the future trend of the stock market, based on a cross-time period, but data snooping problems may appear, which could be solved by the following robustness tests. White (2000) established Reality Check (RC hereafter) to examine whether the benchmark model is superior to those selected technical trading rules. Hansen (2005) supported that RC was not effective since it required to collect too much technical trading rules before the test. Therefore, he developed Superior Predictive Ability (SPA hereafter) using a studentized test statistic and sample-dependent distribution.

Some of the most commonly used technical trading guidelines and indicators are listed below. Joseph E. Granville supported MA reaction as indicators for individual securities. Robert A. Levy (1967) proposed RS to analysis that certain securities perform better than others, and RS could be used in either stocks and bonds.

a) Moving Average Convergence Divergence (MACD hereafter)

Established by Appel (1974), this indicator has been heavily used in the market, where the Moving Average (MA hereafter) is the average level of prices over a given interval of time, smoothing out fluctuations. MA analysis could be widely used for individual securities, market indices, commodity prices (Bodie, Kane and Marcus, 2014), among others. Brock, Lakonishok and Lebaron (1992) reported that trading guidelines based on moving averages provided significant forecast power over the DJIA. Because of its relatively popular measure for individual stocks and the aggregate market, technical analysts tend to examine current prices relative to moving average trend for signals. Simple MA, linear MA and Exponential MA (EMA hereafter) are three main kinds of MA. EMA always reacts more quickly to the last price movements. The MACD shows the difference between the short-term EMA and long-term EMA, plotted against a centerline that two MA are equal. For instance, when the MACD is positive, it signals that the short-term MA is higher than long-term MA, there is a bullish trend with the upward stock price momentum.

b) Relative Strength Index (RSI hereafter)

RS could measure the extent to which a security has outperformed (with a rising ratio) or underperformed (with a decreasing ratio) the whole market (Bodie, Kane, and Marcus, 1992). RSI indicator, created by Welles Wilder (1978), is computed by calculating the ratio of the price of the security to a price index for the industries.

c) KDJ Stochastic Oscillator (KDJ hereafter)

Started in 1954, developed by George Lane in 1984, this is momentum indicators (the %K and %D stochastic Oscillator) that uses support and resistance levels, to predict price turning points. Furthermore, other rules are Trading Range Break (TRB hereafter), Alexander Filter Rules (AF hereafter), Price Pattern Rules (PPR hereafter), Candlestick Rules (CSR hereafter) (Wang and Sun, 2015), etc.

As explained later, in the methodology section, for this thesis I choose to use MA and RSI as technical indicators, which are used to build technical trading guidelines. Firstly, I examine whether technical trading rules could predict Chinese stock market or not. Secondly, if trading rules are not predictable, I analyze which technical indicators, or their combinations could be applied. Thirdly, if trading rules are predictable, I investigate how can I build the strategy based on trading guidelines to outperform the buy-and-hold (B&H hereafter) strategy.

3. Data and methodology

3.1. Data and the data sources

I select two stock indices as data: One is SSE Composite Index (ticker code 000001.SS) from Shanghai stock market, another is SZSE Component Index (ticker code 399001.SZ) from Shenzhen stock market. All historical data of stock indices in recently 21 years (begin from 01/January/1997, end to 13/October/2017), can be downloaded from Yahoo[1], or from RESSET financial research database[2]. Data is expressed in Chinese Yuan currency (CNY).

SSE Composite Index consists of all listed stocks (including A shares and B shares) that are trading at the SSE. It could be more representative to reflect the performance of the Chinese stock market since its trading volume and stock market value were much higher than SZSE's in the past. And SZSE Component Index is an index of 500 constituent stocks (before 2015 it had only 40 stocks) traded at the SZSE.

3.2. Methodology

3.2.1. Establish technical indicators

First, I study the trading strategy established on two classical technical indicators: MA, RSI. I establish 1-indicator trading model based on either MA or RSI, and 2-indicators trading model based on both MA and RSI. Each model uses both Shanghai and Shenzhen stock indices data.

In the 1-indicator trading model, I use the crossing of two MA lines with different time frames as two MA trading rules: MA20, MA50. Here MA20 and MA50 present the moving averages of 20 (short-run moving average periods), or 50 (long-run moving average periods) days closing prices of stock index (Metghalchi, Chang, Garza-Gomez, 2012). Moreover, I use three

1 fr.finance.yahoo.com
2 www.resset.cn

RSI rules: RSI3, RSI9, RSI14, which present the ratio of price movement to the total price movement over 3, 9 or 14-period of days. RSI (equation 1) and RS are shown as below.

$$\mathrm{RSI(n)} = \frac{RS(n)}{1+RS(n)} \times 100 \tag{1}$$

where

$$\mathrm{RS(n)} = \frac{\text{average gain of n days' up closes}}{\text{average loss of n days' down closes}}$$

In a 2-indicators trading model, I make combinations of different MA and RSI: RSI3&MA20, RSI9&MA20, RSI14&MA20, RSI3&MA50, RSI9&MA50, RSI14&MA50.

Investigators use computers calculations to adjust and test several variations of good technical indicators. The values I choose above are the most widely followed. For RSI indicator, n=14 trading days is the default look-back setting suggested (Wilder, 1978), and it is also a must for commodities. For MA indicator, n=9 days of EMA is plotted as the MACD's histogram.

3.2.2. Set up bullish and bearish signals

Second, I set up bullish and bearish signals, based on 1-indicator trading model and 2-indicator trading model.

RSI has a range between 0 (oversold, when below 30) and 100 (overbought, when above 70). The centerline (RSI=50) indicates neutral conditions in the security market. For example, a downward signal is formed when RSI breaks the centerline from above 50 to below 50, and a buy signal is generated when RSI readings above 50. This method is used more comparing to other indicators.

In 1-indicator trading model, it is time to buy when market price breaks through MACD line from below, or when RSI is higher than 50. Then a bullish (or buy) signal will be set up. On the contrary, while market price goes down below MACD line, or when RSI is lower than 50, it is time to sell. Similarly, a bearish (or sell) signal will be set up.

For instance, when two MA lines cross, it signals a change in the overall trend. For MA20 trading rules, if index price crosses MA20 line from below, means a reversal to positive trend, so set up a bullish signal. Particularly, if the upside gap between index price and MA20 lines is too large, it might indicate that the stock is temporarily overbought, and become bearish in the short run (Reilly and Brown, 2006).

In contrast, when index price crosses MA20 line from above, means a change to a negative trend, so set up a bearish signal. If the downside gap becomes larger, it might be considered that the stock is temporarily oversold, which means it will be bullish in the short run (Reilly and Brown, 2006). Similarly, I set up signals for MA50 trading guidelines.

In a 2-indicators trading model, for RSI3&MA20, RSI9&MA20, RSI14&MA20, RSI3&MA50, RSI9&MA50, RSI14&MA50 trading rules, buy signals will be set up, not only when market price breaks through MACD line, but also when RSI is higher than 50. Sell signals will be set up, while market price goes down below MACD line, as well as RSI is lower than 50.

After setting up signals, I calculate next day's return both in the market and out of the market, which will be the difference between the logarithm of the closing price trading day (the t day) and the logarithm of closing price the previous day (the t-1 day), as the equation 2 below.

$$\mathrm{Return(t)} = \ln\frac{P(t)}{P(t-1)} \tag{2}$$

The log return is more commonly used in quantitative finance, compared to arithmetic return. I use the natural logarithm because return could be stable, and approximately equal to the percentage change in the price when the price is not very volatile. Moreover, when modeling the stock market, its continuously compounded period tends to be unlimited, thus logarithmic returns could be assumed as normally distributed.

Daily dividend change could be ignored in the stock index because it does less affect the analysis. Mills and Coutts (1995), as well as Draper and Paudyal (1997) support the idea that dividend exclusion in the results will be minimal.

3.2.3. Test the mean of return

Third, as represented by equation 3, I define the mean buy return (X_B), the mean sell return (X_N), and the mean buy and hold (B&H) return (X_H) of each trading rule I use. I also define the total number of buy days (N_B) and sell days (N_S), the total number of observations days (N). R_B and R_S are the daily returns of buy days and sell days, R is the daily stock returns.

$$X_B = \frac{1}{N_B}\sum_{k=1}^{N_B} R_{Bk}\,,\ X_S = \frac{1}{N_S}\sum_{k=1}^{N_S} R_{Sk}\,,\ X_H = \frac{1}{N}\sum_{k=1}^{N} R_k \qquad (3)$$

I implement t-tests (as shown in equation 4) to determine whether the mean buy or sell returns is different from the mean B&H return, and whether the mean return on buy days is the same as the mean return on sell days (Metghalchi, Chang, Garza-Gomez, 2012). Next, I compare the results from each trading strategy with t-tests, as follows:

$$\begin{aligned} &\text{TEST 1:} \quad \begin{cases} H_0\colon\ X_B - X_H \neq 0 \\ H_A\colon\ X_B - X_H = 0 \end{cases} \\ &\text{TEST 2:} \quad \begin{cases} H_0\colon\ X_S - X_H \neq 0 \\ H_A\colon\ X_S - X_H = 0 \end{cases} \\ &\text{TEST 3:} \quad \begin{cases} H_0\colon\ X_B - X_S \neq 0 \\ H_A\colon\ X_B - X_S = 0 \end{cases} \end{aligned} \qquad (4)$$

Then, following Kwon and Kish (2002), using equation 5 I finish the test statistic for the mean buy return over the mean B&H return (TEST 1). The t-test null hypothesis (H_0) is that the mean buy returns equal to zero. VAR_B and VAR_H represent the variances of the mean of buy return and the mean B&H return respectively. Similarly, by replacing other variables, I test the mean sell return over the mean B&H return (TEST 2), the mean buy return over the mean sell return (TEST 3).

$$\text{t} = \frac{X_B - X_H}{\sqrt{\frac{VAR_B}{N_B} + \frac{VAR_H}{N}}} \qquad (5)$$

4. Empirical results analysis

4.1. Description of the statistical analysis

Tables 1, 2, 3 and 4 display the mean daily returns (X_B, X_S, X_B-X_S), standard deviations of daily returns (SD_B, SD_S), and the number of trades (N, N_B, N_S, total trades) for each trading rule, based on 21 years data of SSE Composite Index and SZSE Component Index. All estimated t-statistics are compared with 1.96, which indicates statistical significance for two-tailed test at the 5% level.

First, I examine whether 1-indicator trading rules can be shown predictable signs. Table 1 reports five trading rules results based on 1-indicator trading model on SZSE Component Index. Analyzing the mean returns of different rules, I observe that: RSI3 > MA20 > RSI9 > RSI14 > MA50. All mean returns are positive with highly significant t-statistics (TEST 1, TEST 2 and TEST 3), which leads to reject the null hypotheses. There are compelling evidences that the mean buy returns is different from the mean B&H returns, the mean sell returns is different from the mean B&H returns, the mean buy returns is different from the mean sell returns, respectively. I conclude that all these trading rules in Shenzhen stock market have predictive power. All mean returns in long position are positive, in short position are negative. Moreover, Shenzhen stock market is more volatile in down market than in up market, because all standard deviations of sell return are bigger than buy return.

Table 2 reports five trading rules results based on 1-indicator trading model on SSE Composite Index. The mean returns of different rules allows to detect that: RSI3 > MA20 > MA50 > RSI14 > RSI9. All mean returns of using MA20, MA50, RSI3 rules are positive with highly significant t-statistics (TEST 1, TEST 2 and TEST 3), so I reject the null hypotheses. Obviously, the mean buy returns is different from the mean B&H returns, the mean sell returns is different from the mean B&H returns, the mean buy returns is different from the mean sell returns, respectively.

For RSI9 and RSI14 rules, the mean B&H return are positive with highly significant t-statistics (TEST 3), rejecting the null hypothesis, but t-tests of the mean buy return (TEST 1) and the mean sell return (TEST 2) are not strong, thus, I accept the null hypothesis. The evidences support that the mean buy returns is not different from the mean B&H returns, the mean sell returns is not different from the mean B&H returns, the mean buy returns is different from the mean sell returns, respectively.

It leads to conclusions that not all trading rules are in predictive power to forecast. All mean returns in long position are positive, in short position are negative. What's more, Shanghai stock market is more volatile in down market than in up market, as all standard deviations of sell return are more than buy return.

Table 1: 1-indicator trading model (SZSE Component Index)

399001.SZ 1-indicator N=5035						
	Buy XB	Sell XS	Buy-Sell XB-XS	Buy SD	Sell SD	Total Trades
MA20	0.0051532	-0.00494	0.000225724	0.016194	0.01892	482
MA50	0.0033291	-0.00298	1.86E-04	0.016904	0.018931	278
RSI3	0.0077038	-0.00752	0.000251768	0.015335	0.017847	1231
RSI9	0.0046169	-0.0045	0.000247837	0.016296	0.019108	662
RSI14	0.0036078	-0.00323	0.00023718	0.017088	0.018812	514
t-stat	TEST 1	TEST 2	TEST 3	Buy NB	Sell NS	
MA20	12.578832	-11.6291	20.25589635	2567	2447	
MA50	7.3922475	-6.90195	12.41447446	2503	2481	
RSI3	18.753256	-17.5757	32.39844349	2569	2462	
RSI9	10.66267	-10.1746	18.12945275	2618	2407	
RSI14	7.9182291	-7.5817	13.47721508	2547	2473	

Table 2: 1-indicator trading model (SSE Composite Index)

000001.SS	**1-indicator**	**N=5043**				
	Buy XB	Sell XS	Buy-Sell XB-XS	Buy SD	Sell SD	Total Trades
MA20	0.0042855	-0.00443	0.000250821	0.013942	0.017637	412
MA50	0.0027284	-0.00259	2.08E-04	0.014446	0.017624	238
RSI3	0.0068181	-0.00693	0.000268467	0.013212	0.016405	1223
RSI9	0.0006956	-0.00025	0.000261804	0.014931	0.017846	670
RSI14	0.0009636	-0.00054	0.000257461	0.015169	0.017542	500
t-stat	TEST 1	TEST 2	TEST 3	Buy NB	Sell NS	
MA20	11.399902	-10.8296	19.21397633	2698	2324	
MA50	6.9270035	-6.51746	11.58191907	2626	2366	
RSI3	18.978964	-17.7249	32.56958838	2639	2401	
RSI9	1.1824624	-1.17735	2.023101691	2732	2301	
RSI14	1.8924749	-1.86841	3.236977291	2672	2356	

Next, I examine whether 2-indicators can improve trading performance. Table 3 reports six trading rules results based on 2-indicator trading model on SZSE Component Index. When I analyze the mean returns of different rules, I find that: RSI3&MA20 > RSI9&MA20 > RSI14&MA20 > RSI3&MA50 > RSI9&MA50 > RSI14&MA50. All mean returns are positive with highly significant t-statistics, leading us to reject the null hypotheses (TEST 1, TEST 2 and TEST 3). It is apparent that the mean buy returns is different from the mean B&H returns, the mean sell returns is different from the mean B&H returns, the mean buy returns is different from the mean sell returns, respectively. I reach the following conclusion that all these trading rules in Shenzhen stock market have predictive power. All mean returns in long position are positive, in short position are negative. In addition, Shenzhen stock market is more volatile in down market than in up market, result from the bigger standard deviations of sell return, compared with the standard deviations of buy return.

Table 4 reports six trading rules results based on 2-indicator trading model on SSE Composite Index. Viewing the mean returns of different rules, I detect that: RSI3&MA20 > RSI3&MA50 > RSI9&MA50 > RSI9&MA20 > RSI14&MA50 > RSI14&MA20. All mean returns are positive with highly significant t-statistics, rejecting the null hypotheses (TEST 1, TEST 2 and TEST 3). Clearly, the mean buy returns is different from the mean B&H returns, the mean sell returns is different from the mean B&H returns, the mean buy returns is different from the mean sell returns, respectively. I draw the conclusion that all these trading rules in Shanghai stock market are predictable. All mean returns in long position are positive, in short position are negative. Besides, Shanghai stock market is more volatile in down market than in up market, since all standard deviations of sell return are greater than buy return.

Table 3: 2-indicator trading model (SZSE Component Index)

399001.SZ	2-indicator	N=5035				
	Buy XB	Sell XS	Buy-Sell XB-XS	Buy SD	Sell SD	Total Trades
RSI3&MA20	0.00468	-0.00444	0.000225	0.016215	0.019158	846
RSI9&MA20	0.003972	-0.00371	0.000225	0.016443	0.019282	565
RSI14&MA20	0.003407	-0.00298	0.000245	0.017052	0.018836	488
RSI3&MA50	0.003065	-0.00271	0.000184	0.016916	0.019019	749
RSI9&MA50	0.002714	-0.00236	0.000185	0.017152	0.018907	463
RSI14&MA50	0.002475	-0.0021	0.000157	0.016863	0.018921	394

t-stat	TEST 1	TEST 2	TEST 3	Buy NB	Sell NS
RSI3&MA20	10.82655	-10.0178	18.14614	2563	2449
RSI9&MA20	9.032708	-8.41446	15.14321	2568	2444
RSI14&MA20	7.426162	-7.0508	12.57842	2531	2480
RSI3&MA50	6.758451	-6.27279	11.30709	2491	2481
RSI9&MA50	5.885528	-5.54663	9.916138	2496	2477
RSI14&MA50	5.423855	-4.93588	8.980902	2440	2507

Table 4: 2-indicator trading model (SSE Composite Index)

000001.SS	**2-indicator**	**N=5043**				
	Buy XB	Sell XS	Buy-Sell XB-XS	Buy SD	Sell SD	Total Trades
RSI3&MA20	0.0039915	-0.0041	0.0002513	0.013956	0.017798	810
RSI9&MA20	0.0018335	-0.00159	2.51E-04	0.014527	0.017912	501
RSI14&MA20	0.0015031	-0.0012	0.000250998	0.014833	0.017679	410
RSI3&MA50	0.0025354	-0.00241	0.000181446	0.014434	0.017697	721
RSI9&MA50	0.0018782	-0.00172	0.000185232	0.014366	0.017767	437
RSI14&MA50	0.0017144	-0.00149	0.000185232	0.014469	0.017674	358
t-stat	TEST 1	TEST 2	TEST 3	Buy NB	Sell NS	
RSI3&MA20	10.561339	-9.99378	17.71785357	2700	2319	
RSI9&MA20	4.3725989	-4.21257	7.357273319	2698	2318	
RSI14&MA20	3.4147006	-3.35393	5.814030224	2693	2323	
RSI3&MA50	6.4470896	-6.0069	10.72088962	2601	2366	
RSI9&MA50	4.6700544	-4.39174	7.774432912	2622	2330	
RSI14&MA50	4.1853708	-3.90162	6.948014362	2591	2361	

4.2. Trading strategies produced higher returns

From the results, most of MA and RSI trading rules are predictable in the Chinese stock market. There is no doubt that these rules forecast better for short-term price movement than long-term price movement, since mean returns: RSI3 > RSI9 > RSI14 and MA20 > MA50. Uncertainty is higher when the holding period increases, thus the predictive power of trading rules would be weakened by a rise in number of holding days. Meanwhile, the number of total trading signal decrease when moving average line become smoother, or the day of price movement goes up. Furthermore, the same trading rules have higher volatilities in short positions than in long positions, because the standard deviation (SD) of buying signals is lower than the SD of selling signals.

Both SSE Composite Index and SZSE Component Index play important roles on the Chinese stock market benchmark, and they have a similar trend. The former mainly reflects the trends of weighted stocks, mostly large companies with higher market-value and liquidity, such as

Sinopec Group, Bank of China, etc. The latter's important proponent are the firms with relatively smaller market capitalization, which have higher risks but higher returns.

1-indicator and 2-indicators trading model with the same position show different results in SSE Composite Index and SZSE Component Index. For example, the mean buy return and mean sell return of Shanghai are lower than Shenzhen, but the mean B&H return of Shanghai is higher than in Shenzhen. The number of buy days in Shanghai stock market is large than Shenzhen stock market. Moreover, SD of Shanghai is smaller than Shenzhen, thus Shanghai stock market is less volatile than Shenzhen stock market. However, these predictive powers in Shanghai stock market are not as strong as that in Shenzhen stock market. Therefore, their forecasting power is better in the medium-market-value stocks than in large-market-value stocks.

This study assumes that short selling is allowed for Chinese investors. In fact, short selling has been limited in the Chinese stock market, so the trading strategies' returns equal to the long position returns. According to most of t-test results of TEST 1 and TEST 2, the mean returns on trading signals are significantly different from the mean daily return, except for RSI9 and RSI14 rules. No matter in Shanghai stock market or Shenzhen stock market, RSI3 is the most excellent 1-indicator trading strategy to defeat B&H strategy, MA20 is the second ranked one. Likewise, RSI3&MA20 is the best 2-indicators investment strategy to beat B&H strategy. Furthermore, according to all t-test results of TEST 3, the long position returns are significantly different from the short position returns. Using RSI3, MA20 or RSI3&MA20 indicator, its sell returns win in Shanghai stock market, and its buy returns win in Shenzhen stock market.

4.3. Chinese Stock Market Indices

Figure 1 and Figure 4 show two similar primary trends in both SSE Composite Index and SZSE Component Index during recent twenty years, with each primary trend revealing three middle waves. Figure 2 and Figure 3 cover historical bubbles periods (2007 and 2015) in

Shanghai stock market respectively. Similarly, Figure 5 and Figure 6 present short time periods in Shenzhen stock market respectively, which could be seen clearly moving averages crossing and trends inversion predicting.

Investors over-react to good news of profitable stocks, as displayed by Chinese stock market indices, which increased rapidly in 2007 and in 2015, revealing momentum effect. However, this effect soon disappeared, and the stock market turbulence occurred in the following year. These irrational reactions resulted from finance and leverage, investors behaviors of overconfidence, and avoiding losses recognition.

For example, in Figure 1, SSE Composite Index outperformed from the beginning of 2006 (close price almost 1000), ended in November 2007 and it became the winner, reached the top (almost 6000). But it turned to be the loser, consequently, it underperformed until December 2008, hitting the global market.

The second stock market bubble happened in January 2016. There is a support trendline between June 2014 and June 2015, when the SSE Composite Index went up and arrived at almost 5000. Then it dropped dramatically with most Chinese investors selling. As a result, there is a resistance trendline during the period from June 2015 to March 2016.

Figure 1. Adjusted close price, MA20 and MA50 of SSE Composite Index

Figure 2. First market bubble in SSE Composite Index

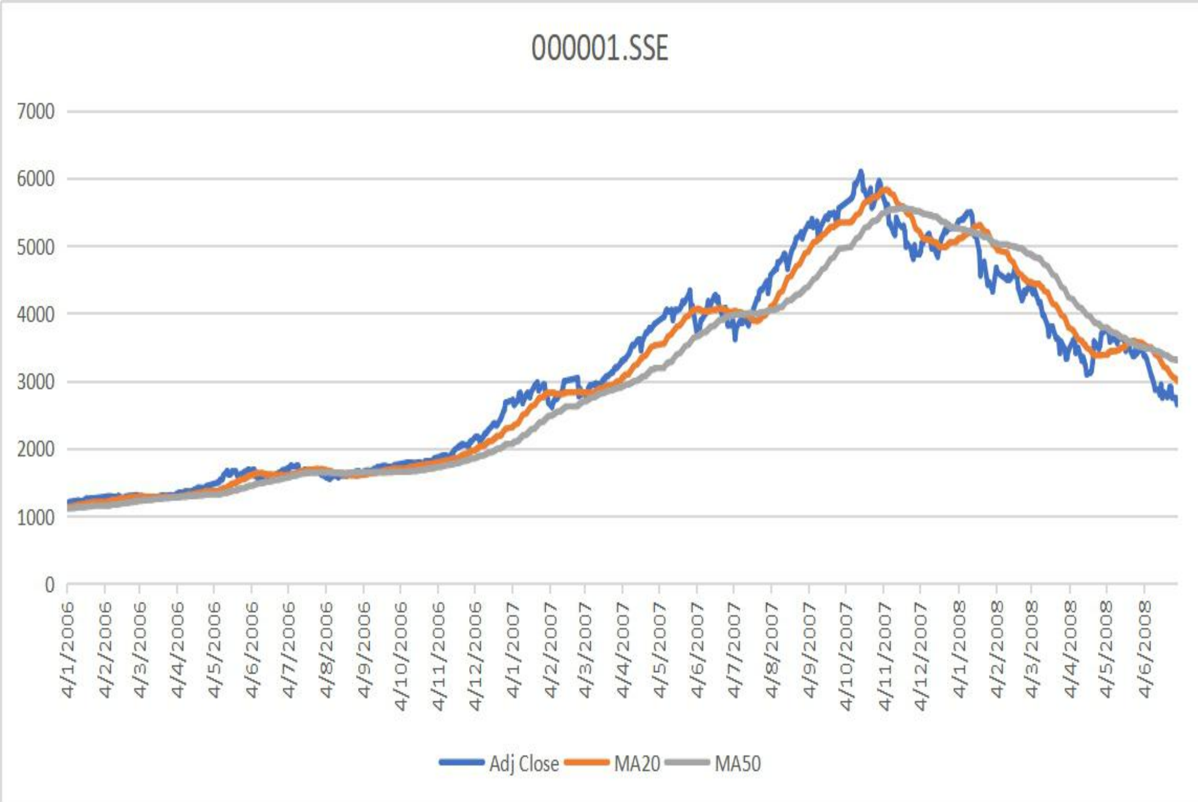

Figure 3. Second market bubble in SSE Composite Index

Figure 4. Adj close price, MA20 and MA50 of SZSE Component Index

Figure 5. First market bubble in SZSE Component Index

Figure 6. Second market bubble in SZSE Component Index

5. Conclusion

Under the Efficient Market Hypothesis (EMH), technical analysis is not supported. Because EMH insists that historical stock data could not predict future price, as all information is already reflected in the current price, prices just follow a random walk. However, technical analysis argues that some trading strategies generate profits when the stock prices have repeated or prominent up and down trends. Profitable opportunities emerge when buy (sell) signals generate positive (negative) returns, and these returns are significantly different from the mean daily returns.

MA20, MA50, RSI3, RSI9, RSI14 as well as their combinations seem to be useful technical indicators. MA smooths and forecasts a period of stocks daily prices, whereas RSI could reflect the momentum effect of stock index. In my thesis, transaction costs are ignored, but they should be considered in real market trading.

From the result of this thesis, most MA and RSI technical trading rules could potentially predict Chinese stock market, since t-tests reject the null hypothesis. This is not observed with RSI9 and RSI14 rules, because their t-tests show that the mean buy return and mean sell return are not significantly different from the mean daily returns.

Furthermore, RSI3 and MA20 emerge as the best and second best predictive 1-indicator signal, for both Shanghai stock market and Shenzhen stock market. The combination of RSI3&MA20 is the best 2-indicators investment strategy to outperform the B&H strategy. However, investors should be out of market quickly at the beginning of stock market bubbles, and they could hold security when stock's up trend started.

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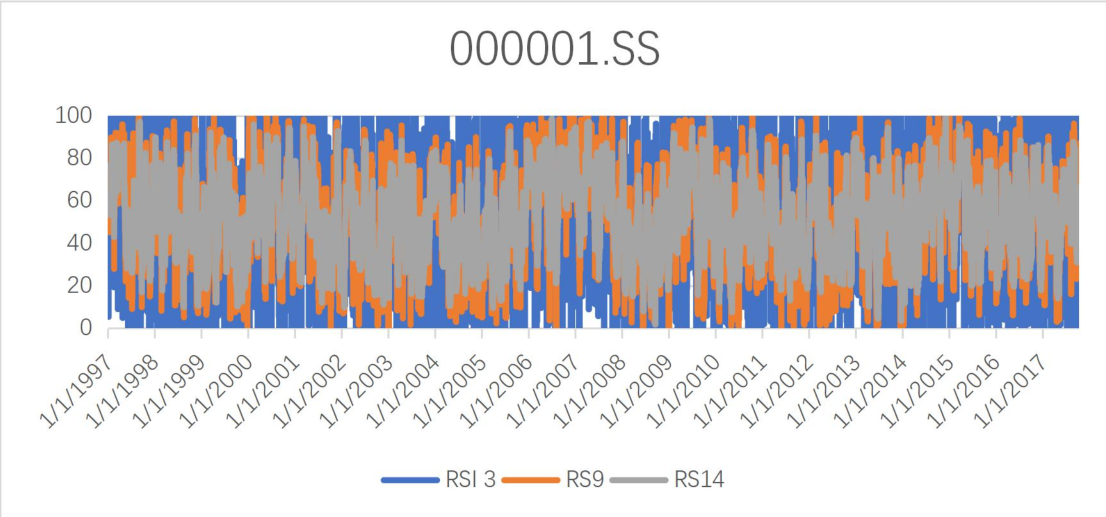
Appendices

I- RSI3, RSI9, RSI14 chart of SSE Composite Index



II- RSI3, RSI9, RSI14 chart of SZSE Component Index