

International Journal of Research in Finance and Management

#### P-ISSN: 2617-5754 E-ISSN: 2617-5762 IJRFM 2019; 2(2): 47-51 Received: 16-05-2019 Accepted: 20-06-2019

#### James J Kung

School of Management, Ming Chuan University, Taipei, Taiwan

### Wen-Ying Lin

College of Humanities & Arts, University of Taipei, Taipei, Taiwan A technical investigation of the shanghai composite index

# James J Kung and Wen-Ying Lin

### Abstract

Using the Shanghai Composite Index from the first trading day in 1998 to the last trading day in 2018, we investigate the effectiveness of two popular technical trading rules (moving average and trading range breakout) in the Chinese stock market. Our results show that, for the two rules, buy signals consistently generate much higher returns than sell signals. In particular, the two rules are quite effective over 1998-2007 but become less effective over 2009-2018. These results suggest that the financial reform and liberalization measures implemented since the 2008 global financial crisis have improved, to a certain degree, the efficiency of the Chinese stock market.

Keywords: Shanghai composite index, moving average, trading range breakout

## 1. Introduction

Technical analysis <sup>[1]</sup> involves the study of historical data to determine future prices on the basis of trends. It does not require the examination of current and past economic news and company information to predict future prices. The first technical analyst was Charles Dow, the creator of the Dow Jones Industrial Average (DJIA), who published his technical analysis in the *Wall Street Journal* in the early 1900s. Technical approach to investing is applicable to stocks, market indices, commodities, futures, or any tradable instruments where price is influenced by the forces of demand and supply. Colby (2002), a noted technical analyst, claimed that technical approach to investment strategy can result in profitable payoff:

For clues to a successful approach one might look to the methods of successful investors or traders. According to an article in Barron's, Richard Dennis of Chicago ran \$1600 into a couple of hundred million in 16 years in the futures market. Dennis is a technician who studies the behavior of the market itself and views the underlying fundamental economic data as largely outdated, already anticipated, or fully discounted by current prices. He carefully follows underlying trends in the empirical trading data and looks for subtle clues of trend change such as market excesses and failures to respond. Dennis began to test all known trading methods. Many methods had to be discarded as obsolete and statistically insignificant. What survived formed the basis of a proprietary set of trading rules that jumps on price breakouts, rides trends, and cuts losses quickly.

This study focuses on the Shanghai Composite Index (SSE Index), which is a stock market index of all stocks <sup>[2]</sup> (A shares and B shares) that are traded on the Shanghai Stock Exchange. The index is based on a base period on a specific base day for its computation <sup>[3]</sup>. The SSE index was launched on 15 July 1991 with a base value of 100. We investigate this index for two reasons. First, financial economists tend to view individual investors as noise traders who, as Black (1986) put it, "trade on noise rather than information." Hence, a market consisting mostly of individual investors can hardly be considered efficient. Since individuals account for the great majority of China's investor population, this study assesses whether some well-known technical trading rules can be used to exploit profit opportunities in such market environment. Second, given that the China Securities Regulatory

Correspondence

James J Kung Wen-Ying Lin School of Management, Ming Chuan University, Taipei, Taiwan

<sup>&</sup>lt;sup>1</sup> See Brock et al., 1992; Bessembinder and Chan, 1998; Siegel, 2002; Kung et al., 2010.

<sup>&</sup>lt;sup>2</sup> A shares are those traded in Chinese Renminbi and B shares are those traded in foreign currencies. Specifically, B shares are traded in US dollars on the Shanghai Stock Exchange whereas B shares are traded in Hong Kong dollars on the Shenzhen Stock Exchange.

<sup>&</sup>lt;sup>3</sup> The base day for the index is 19 December 1990 and the base period is the total market capitalization of all stocks on that day.

Commission implemented, since the 2008 global financial crisis, a series of financial reform and liberalization measures intended to improve market efficiency and competitiveness, this study examines whether these measures have improved, directly or indirectly, the efficiency of the Chinese stock market which, in turn, should have an effect on the effectiveness of the technical rules.

Accordingly, the aim of this study is to investigate, based on daily closing prices of the SSE Index from 1998 to 2018, whether some popular technical trading rules are effective in the Chinese stock market. To proceed, we divide the entire 1998-2018 period into two equal sub-periods (1998-2007 and 2009-2018) and examine if the technical rules have different degrees of effectiveness in the two sub-periods.

The rest of the paper will proceed as follows: Section 2 describes the two technical rules; Section 3 presents summary statistics of the data and describes the hypothesis tests used; Section 4 presents and discusses the empirical results; and Section 5 concludes this study.

# 2. The two technical rules

The two technical trading rules used in this study are moving average (MA) and trading range breakout (TRB). The *n*-day moving average (MA) on day *t* is

$$M_{t,n} = \frac{1}{n} \sum_{k=t-n+1}^{t} P_k = \frac{1}{n} \left[ P_{t-n+1} + P_{t-n+2} + \dots + P_{t-1} + P_t \right] \dots (1)$$

Where  $\Gamma_k$  is the closing price of the index on day k. According to the MA rules, buy and sell signals are emitted by a short MA and a long MA. Buy (sell) signals are emitted when the short MA rises above (falls below) the long MA by a prespecified percentage band. When a signal is emitted, the MA rules require that the position be maintained until the short MA penetrates the long MA again. A popular MA rule is 1-100, where the short MA is one day and the long MA is 100 days. Since most local individual investors trade on short-term basis, such MA rules as 1-20 and 1-50 are often in use. To implement, we use the following MA rules: 1-20, 5-20, 1-50, 2-50, 1-100, and 5-100. Each rule is evaluated with bands of 0% and 1%, making a total of 12 MA rules. Here a band is used to reduce the number of times an investor would have to switch between a long position in the index and a short position in the index. For example, Brock et al. (1992), Bessembinder and Chan (1998), and Siegel (2002) all used a 1% band for their technical rules.

According to the TRB rules, a buy signal is emitted when the current price rises above the local maximum (The maximum price over the past certain number of days) and a sell signal is emitted when the current price falls below the local minimum (The minimum price over the past certain number of days). In notation, an *m*-day local maximum on day *t* and an *m*-day local minimum on day *t* are defined respectively as

$$L\max[m,t] = \max[P_{t-m}, P_{t-m+1}, \dots P_{t-1}]$$

$$L\min[m,t] = \min[P_{t-m}, P_{t-m+1}, \dots P_{t-1}]$$
(2)

$$L\min[m,t] = \min[P_{t-m}, P_{t-m+1}, \dots P_{t-1}]$$
(3)

Where  $P_k$  (k = t-m, t-m+1, ..., t-1) is the closing price of

the index on day k. That is, a buy signal is emitted if  $P_t > L$ max [m, t] and a sell signal is emitted if  $P_t < L \min [m, t]$ . When a buy signal is emitted, the investor takes a long position in the index the next day and maintains the position for ten days. Similarly, when a sell signal is emitted, the investor takes a short position in the index the next day and maintains the position for ten days. In either case, when the ten days are over, the investor starts again waiting for a buy or sell signal. To implement, we use local maximums and minimums over the preceding 20, 50, and 100 days. Again, each rule is evaluated with bands of 0% and 1%, making a total of six TRB rules.

Table 1: Summary statistics for 1-day and 10-day returns

	1998-	1998-	2009-
	2018	2007	2018
Number of observations	5133	2568	2565
Mean 1-day return	0.00019	0.00027	0.00014
$\delta_1(1)$	0.09733	0.07434	0.06432
$\delta_1(2)$	0.01812	-0.04623	0.03437
$\delta_1(3)$	0.08216	0.01041	0.21340
$\delta_1(4)$	0.01023	0.03404	-0.03041
$\delta_1(5)$	0.00302	0.00927	-0.00721
Mean 10-day return	0.00192	0.00267	0.00138
$\delta_{10}(1)$	0.14570	0.15428	0.04639
$\delta_{10}(2)$	0.03286	0.03956	0.01437
$\delta_{10}(3)$	0.00784	-0.02017	0.02831
$\delta_{10}(4)$	-0.01046	0.01105	0.01044
$\delta_{10}(5)$	0.03285	-0.00965	-0.00892

 $\delta_j$  (*i*) is the *i*-day autocorrelation at lag *i* for each series, where *i* = 1, 2, 3, 4, 5 and *j* = 1, 10.

# 3. Summary statistics and hypothesis tests

The data <sup>[4]</sup> used are the daily closing prices of the SSE Index from the first trading day in 1998 to the last trading day in 2018 - a total of 5133 observations. They were drawn from the DataStream database. Results are presented for two equal sub-periods: 1998-2007 and 2009-2018. Table 1 shows summary statistics for the entire period and the two sub-periods for mean 1-day and 10-day returns on the SSE Index. Returns are computed as log differences of the index level. That is,

$$R_{t+j} = \log(P_{t+j}) - \log(P_t) \tag{4}$$

Where  $P_t$  and  $P_{t+j}$  (j = 1, 10) are the closing prices of the index on day t and day t+j, and  $R_{t+j}$  is the return from day t to day t+j. Table 1 shows that the first-order autocorrelations over 1998-2007 are generally larger than those over 2009-2018, which suggests that the stock market over the first sub-period was relatively more at odds with the notion of efficient markets than over the second sub-

<sup>&</sup>lt;sup>4</sup> This study does not include data for the year 2008 because of the irregularities of the stock markets during the 2008 global financial crisis.

period.

A one-sided hypothesis test is used. For buys, the hypothesis is  $H_{01}: \mu_b(j) = \mu(j)$  and the alternative is  $H_{a1}: \mu_b(j) > \mu(j)$ , where  $\mu_b(j)$  is the mean *j*-day return for buys and  $\mu(j)$  is the unconditional mean *j*-day return. The test statistic for buys is

$$Z_{b}(j) = \frac{\overline{r_{b}(j)} - \mu(j)}{\sigma(j)\sqrt{\frac{1}{n_{b}(j)}}}$$
(5)

Where  $r_b(j)$  is the sample mean *j*-day return for buys,  $n_b(j)$  is the number of buy signals, and  $\sigma(j)$  is the *j*-day standard deviation. For sells, the hypothesis is  $H_{02}: \mu_s(j) = \mu(j)$  and the alternative is  $H_{a2}: \mu_s(j) > \mu(j)$ , where  $\mu_s(j)$  is the mean *j*-day return for sells. The test statistic for sells is

$$Z_{s}(j) = \frac{r_{s}(j) - \mu(j)}{\sigma(j)\sqrt{\frac{1}{n_{s}(j)}}}$$
(6)

Where  $r_s(j)$  is the sample mean *j*-day return for sells and  $n_s(j)$  is the number of sell signals. For buys-sells, the hypothesis is  $H_{03}: \mu_b(j) = \mu_s(j)$  and the alternative is  $H_{a3}: \mu_b(j) > \mu_s(j)$ . The test statistic for buys-sells is

$$Z_{b-s}(j) = \frac{\overline{r_b(j) - r_s(j)}}{\sigma(j)\sqrt{\frac{1}{n_b(j)} + \frac{1}{n_s(j)}}}$$
(7)

Given large sample size, all the three test statistics are distributed as N(0,1) if their null hypotheses are true. Accordingly, given the critical normal value  $z_{\alpha}$ , if  $Z_b(j) > z_{\alpha}$ , we reject  $H_{01}$  and conclude that the mean *j*-day return for buys is greater than the unconditional mean *j*-day return at  $\alpha$  significance level. Similarly, if  $Z_s(j) > z_{\alpha}$ , we reject  $H_{02}$  and conclude that the mean *j*-day return for sells is greater than the unconditional mean *j*-day return at  $\alpha$  significance level. In addition, if  $Z_{b-s}(j) > z_{\alpha}$ , we reject  $H_{03}$  and conclude that the mean *j*-day return for buys is larger than the mean *j*-day return for sells at  $\alpha$  significance level. For the three tests, we set the significance level. For the three tests, we set the significance level  $\alpha$  at 1% and 5%.

### 4. Results and Discussion

If the Chinese stock market is efficient <sup>[5]</sup>, then the two technical rules should not be able to yield abnormal returns. Specifically, the mean returns for buy signals (or sell signals) should not differ notably from the corresponding unconditional mean returns. In addition, the mean returns for buy signals should not differ significantly from the mean returns for sell signals. In the following, we will first look at the results for the MA rules and then those for the TRB rules.

## 4.1 MA technical rules

Table 2 shows the results for the MA rules for 1998-2007. For each of the 12 rules, there are more buy signals than sell signals, which suggest that the market tended to drift upward. The mean 1-day returns for buys are all positive with an average 1-day return of 0.00176, which is considerably larger than the unconditional mean 1-day return of 0.00027. Using a one-tailed test, all the 12 rules reject  $H_{01}$  that the mean 1-day returns for buys equal the unconditional mean 1-day return at either 5% or 1% level. Hence, we conclude that the buy signals generated by the 12 rules have obvious predictive power for the 1998-2007 sub-period. In contrast, the mean 1-day returns for sells, although all positive, have an average 1-day return of 0.00082, which is greater than the unconditional mean 1-day return of 0.00027. Using a one-tailed test, we do not reject  $H_{02}$  that the mean 1-day returns for sells equal the unconditional mean 1-day return at either 5% or 1% level. As a result, the Buy-Sell column in Table 2 shows that all the 12 rules reject  $H_{03}$  that the mean 1-day returns for buys equal the mean 1day returns for sells at either 5% or 1% level. Hence, we conclude that the buy signals have more predictive power than the sell signals for the sub-period. In Table 3, the results for 2009-2018 are in sharp contrast to

In Table 3, the results for 2009-2018 are in sharp contrast to those for 1998-2007. The mean 1-day returns for buys are not much different from those for sells, with an average 1-day return of 0.00039 for buy signals and 0.00034 for sell signals. Using a one-tailed test, none of the 12 technical rules reject  $H_{01}$  (or  $H_{02}$ ) that the mean 1-day returns for buys (or sells) equal the unconditional mean 1-day return of 0.00014 at either 5% or 1% significance level.

# 4.2 TRB technical rules

Table 4 reports the results for the TRB rules for 1998-2007. Again, for each of the six technical rules, the mean 10-day returns for buys are all positive with an average 10-day return of 0.02458, which is considerably larger than the unconditional mean 10-day return of 0.00267. Using a one-tailed test, all the six rules reject  $H_{01}$  that the mean 10-day return of 0.00267 at 1% level. In contrast, the mean 10-day returns for sells have an average 10-day return of only 0.001303. Naturally, the Buy-Sell column in Table 4 shows that all the six rules reject  $H_{03}$  that the mean 10-day returns for buys

<sup>&</sup>lt;sup>5</sup> See Fama, 1970 and 1991; Marshall and Cahan, 2005; Metghalchi et al., 2008.

equal the mean 10-day returns for sells at either 5% or 1% significance level. Hence, we conclude that buy signals possess more predictive power than sell signals for this sub-period.

In Table 5, the results for 2009-2018 are again noticeably different from those for 1998-2007. The average 10-day

return is 0.00282 for buys and -0.00186 for sells. Based on a one-tailed test, none of the six rules reject  $H_{01}$  (or  $H_{02}$ ) that the mean 10-day returns for buys (or sells) equal the unconditional mean 10-day return of 0.00138 at either 5% or 1% significance level.

Table 2: Results for moving average rules: 19	98-2007
---	---------

Rule	n(Buy)	n(Sell)	Buy	Sell	Buy-Sell
(1, 20, 0%)	1361	1175	0.00192 (4.61886)**	0.00142 (2.15394)*	0.00050 (1.47802)
(5, 20, 0%)	1385	1144	0.00163 (3.12574)**	0.00081 (0.79624)	0.00082 (1.76914)*
(1, 50, 0%)	1314	1189	0.00192 (3.38851)**	0.00096 (1.27459)	0.00096 (1.55126)
(5, 50, 0%)	1325	1172	0.00168 (3.50423)**	0.00082 (0.69765)	0.00086 (1.81802)*
(1, 100, 0%)	1374	1166	0.00160 (2.72091)**	0.00063 (0.34857)	0.00073 (1.69518)*
(5, 100, 0%)	1353	1118	0.00151 (2.26530)**	0.00052 (0.05560)	0.00099 (1.87076)*
(1, 20, 1%)	1372	1098	0.00224 (3.64518)**	0.00122 (1.90143)*	0.00102 (1.77152)*
(5, 20, 1%)	1321	1118	0.00187 (3.65037)**	0.00083 (0.67683)	0.00104 (2.12023)*
(1, 50, 1%)	1363	1174	0.00201 (3.75873)**	0.00089 (1.24430)	0.00112 (1.85402)*
(5, 50, 1%)	1348	1137	0.00173 (3.69092)**	0.00074 (0.47878)	0.00099 (2.23054)*
(1, 100, 1%)	1385	1126	0.00160 (2.76423)**	0.00068 (0.50573)	0.00092 (1.39192)
(5, 100, 1%)	1376	1167	0.00142 (2.47625)**	0.00035 (-0.30889)	0.00107 (1.88416)*
Average			0.00176	0.00082	0.00094

Figures in parentheses are standard z values testing the difference of mean buy 1-day return (or mean sell 1-day return) from unconditional mean 1-day return, and that of mean buy-sell 1-day return from 0. Figures with \* (\*\*) are significant at 5% (1%) level for a one-tailed test.

Table 3: Results for moving average rules: 2009-2018

Rule	n(Buy)	n(Sell)	Buy	Sell	Buy-Sell
(1, 20, 0%)	1334	1194	0.00018 (-0.51427)	0.00013 (-0.59722)	0.00005 (0.16323)
(5, 20, 0%)	1323	1183	0.00023 (-0.68465)	0.00005 (-0.77146)	0.00018 (0.16733)
(1, 50, 0%)	1317	1136	0.00057 (0.57757)	0.00067 (0.52225)	-0.00010 (-0.04854)
(5, 50, 0%)	1322	1135	0.00045 (-0.11325)	0.00042 (-0.08671)	0.00003 (-0.01826)
(1, 100, 0%)	1336	1147	0.00031 (-0.31321)	0.00029 (-0.31128)	0.00002 (0.03245)
(5, 100, 0%)	1327	1173	0.00035 (0.03665)	0.00048 (0.05540)	-0.00013 (-0.01521)
(1, 20, 1%)	1128	1084	0.00048 (0.07456)	0.00036 (-0.14342)	0.00012 (0.16123)
(5, 20, 1%)	1146	976	0.00021 (-0.61082)	0.00010 (-0.61701)	0.00011 (0.04176)
(1, 50, 1%)	1282	1142	0.00071 (0.59183)	0.00055 (0.37477)	0.00016 (0.13692)
(5, 50, 1%)	1274	1121	0.00045 (0.01119)	0.00027 (-0.21237)	0.00018 (0.18218)
(1, 100, 1%)	1275	1129	0.00040 (-0.09772)	0.00028 (-0.18517)	0.00012 (0.07509)
(5, 100, 1%)	1225	1133	0.00036 (-0.07567)	0.00042 (0.05514)	-0.00006 (-0.09028)
Average			0.00039	0.00034	0.00005

Figures in parentheses are standard z values testing the difference of mean buy 1-day return (or mean sell 1-day return) from unconditional mean 1-day return, and that of mean buy-sell 1-day return from 0.

Table 4: Results for trading range breakout rules: 1998-2007

Rule	n(Buy)	n(Sell)	Buy	Sell	Buy-Sell
(10, 20, 0%)	132	87	0.02277 (2.30762)**	0.01323 (0.93570)	0.00954 (0.94284)
(10, 50, 0%)	97	56	0.02352 (2.19328)*	0.01082 (0.22155)	0.01270 (1.23643)
(10, 100, 0%)	68	33	0.02671 (2.23945)*	0.01392 (0.58179)	0.01279 (0.93679)
(10, 20, 1%)	91	56	0.02503 (2.34321)**	0.01634 (1.01786)	0.00869 (0.87923)
(10, 50, 1%)	55	48	0.03134 (2.45663)**	0.01102 (0.18856)	0.02032 (1.28787)
(10, 100, 1%)	68	35	0.03012 (2.21037)*	0.01284 (0.44805)	0.01728 (1.24283)
Average			0.02658	0.01303	0.01355

Figures in parentheses are standard z values testing the difference of mean buy 10-day return from unconditional mean 10-day return, and that of mean buy-sell 10-day return from 0. Figures with \* (\*\*) are significant at 5% (1%) level for a one-tailed test.

Table 5: Results for trading range breakout rules: 2009-2018

Rule	n(Buy)	n(Sell)	Buy	Sell	Buy-Sell
(10, 20, 0%)	96	87	0.00441 (0.27235)	0.00053 (-0.09161)	0.00388 (0.28312)
(10, 50, 0%)	84	67	0.00203 (0.18065)	-0.00662 (-1.18363)	0.00865 (1.02742)
(10, 100, 0%)	62	43	0.00284 (0.28213)	-0.00190 (-0.32211)	0.00474 (0.43243)
(10, 20, 1%)	64	63	0.00313 (0.32988)	0.00062 (-0.04231)	0.00375 (0.28192)
(10, 50, 1%)	53	56	0.00172 (0.11294)	-0.00232 (-0.47012)	0.00404 (0.60122)

	(10, 100, 1%)	34	30	0.00278 (0.22334)	-0.00144 (-0.23129)	0.00422 (0.29851)	
Γ	Average			0.00282	-0.00186	0.00468	
	Figures in parentheses are standard z values testing the difference of mean buy 10-day return (or mean sell 10-day						

return) from unconditional mean 10-day return, and that of mean buy-sell 10-day return from 0.

# 5. Conclusion

In an efficient market, publicly known investment strategies or rules cannot be expected to yield abnormal returns. In this study, we use two well-known technical trading rules to evaluate their effectiveness in the Chinese stock market. Our results show that, for the two rules, buy signals consistently generate much higher returns than sell signals. In particular, the two rules are quite effective over 1998-2007 but become less effective over 2009-2018. These results suggest that the financial reform and liberalization measures implemented since the 2008 global financial crisis have improved the efficiency of the Chinese stock market.

## 6. References

- Bessembinder H, Chan K. "Market Efficiency and the Returns to Technical Analysis." Financial Management, 1998; 27(2):5-17.
- Black F. "Noise." Journal of Finance. 1986; 41:529-543.
- 3. Brock W, Lakonishok J, LeBaron B. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. Journal of Finance. 1992; 47:1731-1764.
- 4. Colby RW. The Encyclopedia of Technical Market Indicators, McGraw-Hill, New York, 2002.
- Fama EF. Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance, 1970; 25:383-417.
- 6. Fama EF. Efficient Capital Markets: II. Journal of Finance. 1991; 46(5):1575-1617.
- Kung JJ, Carverhill AP, McLeod RH. Indonesia's Stock Market: Evolving Role, Growing Efficiency. Bulletin of Indonesian Economic Studies. 2010; 46(3):329-346.
- 8. Marshall BR, Cahan RH. Is Technical Analysis Profitable on a Stock Market which has Characteristics that suggest it may be Inefficient? Research in International Business and Finance. 2005; 19:384-398.
- 9. Metghalchi M, Chang YH, Marcucci J. Is the Swedish Stock Market Efficient? Evidence from Some Simple Technical Rules. International Review of Financial Analysis. 2008; 17:475-490.
- 10. Siegel JJ. Stocks for the Long Run, third edition, McGraw-Hill, New York, 2002.