

The Chinese Stock Market: An Examination of the Random Walk Model and Technical Trading Rules

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Using the variance ratio test, we reject the random walk null hypothesis for class A and class B stock market indexes traded on the Shanghai and Shenzhen stock exchanges. Consistent with this result, we find that the ARIMA forecasting model generates more accurate forecasts as compared to the naïve model based on the random walk assumption. We also observe significant positive returns for individual stocks after transaction costs on buy trades generated by the contrarian version of three commonly used technical trading rules: the moving average crossover rule, the channel breakout rule, and the Bollinger band breakout rule.

Introduction

Considerable academic research has been conducted on the effectiveness of technical analysis of the stock and futures markets. Proponents of the random walk theory (Samuelson, 1965; and Fama, 1965, 1970, 1995) believe that price fluctuations occur randomly; therefore, it is futile for technical analysts to try to predict the future based on previous price action. Malkiel (1981) summarizes the academic position: “Technical analysis is anathema to the academic world. We love to pick on it. And while it may seem a bit unfair to pick on such a sorry target, just remember: it is your money we are trying to save.” Despite these disparaging pronouncements

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from the ivory towers of academia, it appears that technical analysis is alive and doing just fine on Wall Street. Increasing amounts of time and energy are being expended by brokerage houses in trying to uncover the Holy Grail of technical analysis formulas or chart patterns to predict future prices based on current and past prices.

In an attempt to resolve this dilemma, several empirical studies have tried to establish the efficacy of technical analysis by answering two basic questions: (a) Does the random walk model capture the reality of stock market price fluctuations? and (b) Can technical trading rules or charting techniques consistently generate better than chance predictions of stock prices? Earlier studies by Alexander (1961), Fama and Blume (1966), Levy (1967), Jensen (1967), and Jensen and Bennington (1970) show that technical analysis is essentially useless. More recent studies by Sweeney (1988) and Brock et al. (1992) suggest that these pronouncements on the futility of technical analysis might have been premature and not entirely accurate. Sweeney (1988) extends the Fama and Blume (1966) study and concludes that the filter rules used by Fama and Blume could be used to generate a profit; however, this profit is sensitive to transactions costs and the bid-ask spread. Brock et al. (1992) employ data from the Dow Jones Industrial Average from the first day of trading in 1897 to the last day of trading in 1986, a collection of 90 years of daily data. They test two of the simplest and most commonly used technical trading rules and conclude that these trading rules did provide strong support for technical strategies, especially for buy signals.

More recent research has studied the effectiveness of technical analysis in emerging stock markets in the Far East. For example, Bessembinder and Chan (1995) examine the validity of technical trading rules in Hong Kong, Korea, Japan, Malaysia, Taiwan, and Thailand from 1975 to 1991. They find that technical trading rules possess strong forecast ability for the emerging markets of Malaysia, Taiwan, and Thailand. This view is confirmed by Lai et al. (2003), who examine daily stock prices for the Kuala Lumpur Stock Exchange (KLSE) Composite Index from January 1977 to December 1999 and find that prices behave in a non-random fashion. They find that technical trading rules generate significantly positive returns, even after considering transaction costs.

Coutts and Cheung (2000) find that whereas the moving average and channel breakout rules generate marginal abnormal returns for the Hang Seng index between 1985 and 1997 before considering transaction costs, these excess returns disappear for the moving average crossover rule after considering transaction costs. Previous research on the efficiency of China's stock markets has not yielded conclusive results. Liu, Song, and Romily (1997), Laurence, Cai, and Qian (1997), and Long, Payne, and Feng (1999) study aggregate stock market indexes in China and find evidence in support of weak-form efficient market hypothesis (EMH). A similar

conclusion is reached by Li and Chen (2003) using individual stock price and volume data for 39 companies listed on the Shenzhen stock exchange.

On the other hand, Mookerjee and Yu (1999) run a battery of parametric and non-parametric tests before concluding that there are significant inefficiencies on both the Shanghai and Shenzhen stock exchanges.

Within the context of this rather confusing backdrop, it is the goal of this paper to test (a) the null hypothesis that Chinese stock prices follow a random-walk process, and (b) the profitability or lack thereof of three technical trading rules as applied to the emerging Chinese stock market.

The Background of the Chinese Stock Market

The embryonic Chinese stock markets have attracted much attention because of that country's rapid economic growth and the desire of foreign investors to participate in potential growth at the ground floor level. Beginning in 1978, the goal of China's economic reforms was to transform the economy from a centrally-planned economy to one that was market-based. Accordingly, state-owned enterprises were authorized to issue a predefined mix of five classes of shares: shares owned by the state, legal person shares, employee shares, class A shares, and class B shares. A small group of Chinese firms also were authorized to issue shares that are listed and traded overseas, such as H-shares traded in the Hong Kong Stock Exchange and N-shares which are traded on the New York Stock Exchange. State shares, legal person shares, and employee shares are not tradable. About two-thirds of all outstanding shares are not publicly tradable. Only class A and class B shares are authorized for public trading on the two major Chinese stock exchanges: the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SHZE) which were established on December 19, 1990, and April 3, 1991, respectively. Whereas class A shares were open for trading upon the establishment of the two exchanges, class B shares were offered for trading some years later.

Class A shares were meant to be traded by domestic Chinese citizens. As mentioned by Green (2003), there are only a handful of institutional investors in China's class A markets. Class B shares initially were meant to be traded by foreign legal or natural persons and Chinese nationals living overseas. Since July 1, 2001, however, individual domestic investors are allowed to own and trade class B shares listed on the Shanghai and Shenzhen Stock Exchanges. While class A shares listed on both exchanges are denominated in local Chinese People's Currency, the Renminbi or RMB, class B shares listed on the Shanghai Stock Exchange are denominated in US dollars, and class B shares listed on the Shenzhen Stock Exchange are denominated in Hong Kong dollars. Although class A and class B shares are entitled by law to the same rights and privileges, it has been observed by multiple researchers (Chen, Lee, and Rui, 2001; Long, Payne, and Feng, 1999; and Su, 1999) that class B shares sell for a large discount relative to class A shares for the same company. Information

asymmetry (Chui and Kwok, 1998) and differential risk aversion (Ma, 1996) have been suggested as possible reasons for this phenomenon. Additionally, firms with class B shares outstanding are subject to more stringent financial reporting and auditing standards. Whereas firms with class A shares outstanding are required to prepare financial statements in accordance with Chinese accounting standards, which are significantly less comprehensive than those of industrialized countries, firms with class B shares outstanding have the additional responsibility of preparing their accounts in accordance with Chinese and International Accounting Standards and must have their financial statements audited by international accounting firms.

On December 31, 1991, China had a total of 14 listed stocks, of which eight were listed on the Shanghai stock exchange and six were listed on the Shenzhen stock exchange. As of December 31, 1997, there were a total of 720 A-shares, of which 372 were listed on the Shanghai exchange and 348 were listed on the Shenzhen exchange. In addition, there were a total of 96 B-shares. As of December 31, 2004, there were a total of 1340 A-shares, of which 822 were listed on the Shanghai exchange and 518 were listed on the Shenzhen exchange. In addition, there were a total of 109 B-listed shares, of which 54 were listed on the Shanghai stock exchange and 55 on the Shenzhen stock exchange.

According to the Shanghai and Shenzhen Stock Exchange Fact Book (2004 edition), the overall Chinese stock market capitalization has increased from RMB 10.92 billion on December 31, 1991, to RMB 1752.93 billion on December 31, 1997, and further to RMB 3705.55 billion as of December 31, 2004. Despite this tremendous growth, the Chinese stock markets still lack the depth and maturity of stock markets in developed countries. As observed by Green (2003), China's market capitalization as a proportion of its GDP was about 45 percent, whereas the corresponding figure for the United States was over 300 percent. Moreover, Chinese stock markets are influenced by exogenous shocks resulting from the government's market intervention policies and from sudden changes in governmental stock-market regulation. As discussed by Su and Fleisher (1998) and Green (2003), these shocks result in greater speculative activity on the Chinese stock exchanges, resulting in significantly higher stock market volatility.

Data and Methodology

For the purposes of this research, we analyze the index of daily stock prices for all class A and class B shares trading on both the Shanghai and Shenzhen stock exchanges. We analyze daily data for the Shanghai stock market index for class A shares from December 19, 1990 to June 27, 2005, representing a total of 3567 observations, and for class B shares from February 21, 1992 to June 27, 2005, representing a total of 3268 observations. Similar data for the index of class A shares trading on the Shenzhen exchange are analyzed from April 3, 1991 to June 27, 2005,

representing a total of 3476 observations, and for class B shares from December 19, 1995 to June 27, 2005, representing a total of 2295 observations.

We begin by examining the skewness, kurtosis, and normality of daily returns for each of the four indexes above. Next, we check whether prices follow a random walk model in each of the four indexes by using the variance ratio test developed by Lo and MacKinlay (1988). If prices follow the random walk null hypothesis, the variance of first differences of a time series increases linearly, such that the variance over q -lags is simply q times the variance of the first difference over one lag. The variance ratio (VR) is written as follows:

$$VR(q) = \frac{\sigma_q^2}{q \cdot \sigma^2}$$

Where, σ_q^2 is the variance for the q th difference in stock prices and σ^2 is the variance of the one-period difference in stock prices. The null hypothesis is that the variance ratio is 1 under the random walk assumption. The variance ratio test employs two standard normal test statistics, $z(q)$ and $z^*(q)$, which test the null hypothesis of random walk under the assumptions of homoscedasticity and heteroscedasticity, respectively. Let us assume that there are $(nq+1)$ observations of daily returns, where q is any integer greater than 1. The first statistic, $z(q)$, assumes an independent and identically distributed normal error term and is defined as follows:

$$z(q) = [VR(q) - 1] / \sqrt{\{[2(2q - 1)(q - 1)] / 3q(nq)\}} \approx N(0,1)$$

The second test statistic, $z^*(q)$, relaxes the assumption of homoscedasticity and corrects for heteroscedasticity of the error terms, and is defined as follows:

$$z^*(q) = [VR(q) - 1] / \sqrt{\{\Phi^*(q)\}} \approx N(0,1)$$

$\Phi^*(q)$ is the variance term consistent with heteroscedasticity and is computed as follows:

$$\Phi^*(q) = (4 \sum_{k=1}^{q-1} [1 - (k/q)] \delta_k) / nq$$

where:

$$\delta_k = [nq \sum_{j=k+1}^{nq} (p_j - p_{j-1} - \mu)^2 (p_{j-k} - p_{j-k-1} - \mu)^2] / [\sum_{j=1}^{nq} (p_j - p_{j-1} - \mu)^2]^2$$

After completing the variance ratio test for randomness in Chinese stock prices, we seek to verify our results by studying the predictability of Chinese stock prices. We generate ex post forecasts of daily prices using a naïve forecasting model and an autoregressive integrated moving average (ARIMA) model. The naïve forecasting model maintains that the market follows a random walk process and that the current period's price provides the best estimate of the next period's price. If Chinese stock prices do follow a random walk process, forecasts based on the naïve model should

be just as effective as those generated by the more sophisticated ARIMA forecasting model. The ARIMA model is described in terms of its (p, d, q) coefficients, where p denotes the number of autoregressive (AR) terms, d denotes the number of times the series has to be differenced before it becomes stationary, and q denotes the number of moving average (MA) terms.

Following Darrat and Zhong (2000), we use the logarithmic first differences of prices in both the naïve and ARIMA forecasting models to predict out-of-sample prices five trading days (or one week) in the future. We employ the iterative process suggested by the Box-Jenkins (1978) methodology to ascertain the optimal values for p, d, and q. Using this approach, we find that the time series for class A shares traded on both the Shanghai and Shenzhen stock exchanges are best represented by the ARIMA(1,1,1) model, whereas the time series for class B shares traded on both the Shanghai and Shenzhen stock exchanges are best represented by the ARIMA(1,1,3) model.

Accordingly, these ARIMA models are used to generate forecasts. We use three different test statistics to measure the accuracy of our forecasts: the root mean squared error (RMSE), the mean absolute error (MAE), and Theil's U.¹ If the forecasting error is approximately equal for the naïve and ARIMA forecasting approaches, this would suggest that prediction is difficult in the absence of a well-defined pattern and that prices follow a random walk process. Alternatively, a smaller forecasting error for the ARIMA model as compared to the naïve model would suggest that there is a well-defined pattern captured by the ARIMA model and that prices do not follow a random walk process.

Finally, using the China Stock Market (CSMAR) database of daily individual stock prices, we investigate the profitability of three commonly used technical trading rules relative to the buy-and-hold strategy for all class A and class B stocks traded on the Shanghai and Shenzhen stock markets from inception date through December 31, 2004. The three rules analyzed here are the dual moving average crossover rule, the channel breakout rule, and the Bollinger band breakout rule. We explain the logic of each these three technical trading rules below. To replicate real-life trading conditions in China, we add a transaction fee of 0.5 percent to the purchase price and subtract the same amount from the sale price of each trade to arrive at the profit for a given trade. According to the information provided on the websites of the Shanghai and Shenzhen stock exchanges, the current trade commission is 0.4 percent for both class A and B shares traded in the Shanghai and Shenzhen exchanges, including a 0.1 percent stamp tax charged for all purchases and sales.

¹ These test statistics of forecasting efficiency are defined by Greene (2000) as follows:

$RMSE = \sqrt{1/T \sum (P^* - P)^2}$;

$MAE = 1/T \sum |P^* - P|$; and

$Theil's\ U = \sqrt{1/T \sum (P^* - P)^2} / \sqrt{1/T \sum P^2}$,

where P^* = forecast price, P = actual price, T = number of forecast horizons.

Additionally, there is a trust fee of 0.05 percent for class B shares traded in both Shanghai and Shenzhen markets, and a hand-change fee of 0.1 percent for trades involving Shanghai class A shares. Therefore, the total transaction cost is 0.5 percent for Shanghai class A shares, 0.4 percent for Shanghai class B shares, and 0.45 percent for Shanghai and Shenzhen class B shares. To simplify our calculations, and in the interests of conservatism, we have considered the highest fee of 0.5 percent for all class A and class B shares transacted in both the Shanghai and Shenzhen markets. Moreover, as the Chinese government has banned the short sale of stocks, we ignore all short-sell signals generated by each of the trading rules and only present our results for all buy trades.

The dual moving average crossover rule compares the values of two moving averages with differing lag lengths, x and y . An x -day moving average is the arithmetic average of close prices for the current and previous $(x-1)$ days. Similarly, a y -day moving average is the arithmetic average of close prices for the current and previous $(y-1)$ days. The lag length y is selected to be greater than the lag length x . It is called a moving average because the earliest observation is discarded each day as a new observation is included. The conventional users of this rule believe in the existence of long-term price trends, and they further believe that a new long-term trend is triggered when the short-term moving average closes above (below) the long-term moving average. Accordingly, the conventional application of the dual moving average crossover rule recommends buying (selling) at the close price of the trading day immediately after the short-term moving average, x , exceeds (falls below) the long-term moving average, y , by at least 1 percent. The 1 percent band filters false signals due to the whiplash effect of prices. Market contrarians do not believe in the existence of long-term trends, however, and therefore find value in doing the exact opposite of their trend-following counterparts, i.e. selling (buying) at the close price of the trading day immediately after the short-term moving average, x , exceeds (falls below) the long-term moving average, y , by at least 1 percent. Contrarians believe that any deviation from a long-term moving average is purely temporary and is likely to be followed by a price reversal. This is particularly true in volatile stock markets. Given the significant volatility of the Chinese stock market, we elect to use the contrarian approach for our research, marking a departure from the conventional approach used by Coutts and Cheung (2000) and Lai et al. (2003). Specifically, we use lag lengths of five and 20 for the short-term moving average, x , and lag lengths of 60, 120, and 180 for the long-term moving average. Hence, we have a total of six combinations of moving average crossover rules: (5, 60), (5,120), (5,180), (20, 60), (20,120), and (20,180).

The conventional wisdom for the channel or trading range breakout rule, as espoused by long-term trend followers, is that a new long-term trend develops when prices close above (below) the highest high (lowest low) of the previous n days. Accordingly, a buy (sell) signal is generated at the close price of the following day if

the close price for any given day exceeds (falls below) the highest (lowest) close price of the past n -days by at least 1 percent. The 1 percent band serves to filter false breakouts. Market contrarians, who do not believe in the existence of long-term trends, maintain that a price breakout is simply the precursor to a price reversal and therefore find value in doing the exact opposite: a buy (sell) signal is generated for the following day's close if the close price on any given day falls below (exceeds) the lowest (highest) close price of the past n -days by at least 1 percent. Consistent with our strategy in the moving average rule, we elect to work with the contrarian approach for our research, using the following six arbitrarily selected values, n , for the look-back period: 20, 40, 60, 120, 150, and 180 days.

The Bollinger band rule outlined in Bollinger (2002), defines an x -standard deviation band above and below the n -day moving average of historic close prices. The trend-following version of this rule assumes that prices will continue to move in the direction of the penetration, i.e., a penetration of the upper (lower) band suggests that prices will continue to move higher (lower), implying a buy (sell) signal. Market contrarians feel that a penetration of the upper (lower) band is symptomatic of an over-reaction of prices with a strong possibility of an impending trend reversal, thereby suggesting a sell (buy) signal. Consistent with our strategy in both the moving average and channel breakout rules, we adopt the contrarian approach for our research. We define a two standard deviation band above and below the n -day moving average of close prices, where n is defined to be 20, 40, 60, 120, 150, or 180 days. If the close price today exceeds (falls below) the upper (lower) band, we have a sell (buy) signal at the close price on the following day.

Empirical Results

Table 1 provides a summary of the statistical properties of daily returns for both the class A and class B stock indexes traded on the Shanghai and Shenzhen stock exchanges. For the Shanghai stock exchange, the percentage mean returns and standard deviations are higher for the index of class A shares as compared to the index of class B shares. In the case of the Shenzhen stock exchange, the percentage mean returns and standard deviations are higher for the index of class B shares as compared to the index of class A shares. The standard deviation for each of the four indexes is above 2.2375, with the highest value of 3.0878 occurring for the Shanghai index of class A shares. These values are much higher than the standard deviation of 1.6123 reported by Coutts and Cheung (2000) for the Hang Seng index between 1985 and 1996 and the standard deviation of 1.5959 reported by Lai et al. (2003) for the Kuala Lumpur Stock Exchange Composite Index between 1977 and 1999. This suggests a much higher level of volatility in the Chinese stock markets as compared to Malaysia or Hong Kong and confirms the findings of Su and Fleisher (1998) and Green (2003). Moreover, all four indexes show that the distributions are not normal. Each of the four indexes displays positive skewness, indicating that the returns are

not symmetrically distributed. The positive skewness is more pronounced in class A shares as compared to class B shares for both the Shanghai and Shenzhen markets. Again, the positive skewness for the Chinese markets differs from the negative skewness reported by Coutts and Cheung (2000) for the Hang Seng index and the negative skewness reported by Lai et al. (2003) for the Malaysian market. Similarly, the kurtosis measure is positive for each of the four indexes, indicating that the returns are peaked or leptokurtic.

Table 1—Descriptive Statistics of Daily Returns on Chinese Stock Indexes

Index	N	% Mean	Std Dev	Skewness	Kurtosis	Normal Dist
Shanghai Index -- A shares	3566	0.1084	3.0878	12.3162	389.1150	0.1856
Shanghai Index -- B shares	3267	0.0052	2.2377	0.6457	5.5888	0.1147
Shenzhen Index -- A shares	3475	0.0601	2.4261	1.3236	18.2602	0.1161
Shenzhen Index -- B shares	2294	0.0878	2.5087	0.4862	5.3455	0.1224

Notes: This table reports a summary of the statistical properties of daily returns for the Shanghai, and Shenzhen stock indexes. N is the number of observations. %Mean is the average daily return. Std Dev is the standard deviation. Normal Dist measures the existence of a normal distribution of returns

Panels (A) through (D) of Table 2 present the variance ratio test results applied to daily stock price data for the four major Chinese stock market indexes for lag lengths ranging from two to 24 days. In each of the Panels in Table 2, we find that the variance ratio is greater than one, and the variance ratio increases with an increase in the lag length. Upon comparison of the variance ratios for the index of class A shares traded, we find that the ratios are higher for the Shenzhen market as compared to the Shanghai market, signifying greater autocorrelation of returns in the Shenzhen market for class A shares. Moreover, for any given lag length, the variance ratios are higher for the index of class B shares as compared to class A shares. This is true for both the Shanghai and Shenzhen exchanges. This suggests that the daily stock price series is first-order autocorrelated or non-random, and the autocorrelation is greater in case of class B shares as compared to class A shares. For example, in the case of the Shanghai stock exchange, the variance ratio for a lag length of two days is 1.0562 for the index of class A shares, and 1.1631 for the index of class B shares. This implies a first-order autocorrelation of 5.62 percent for the index of class A shares, and a much higher 16.31 percent for the index of class B shares. Using the $z(q)$ statistic which assumes homoscedasticity of the error terms, we reject the random walk null hypothesis at the 5 percent level of significance for lag lengths up to six days for the Shanghai class A stock index and for lag lengths up to ten days for the Shanghai class B stock index. Similarly, the random walk null hypothesis is rejected under the assumption of homoscedasticity of the error terms for lag lengths of up to 8 days for the Shenzhen class A stock index and for lag lengths of up to 14 days for the Shenzhen class B stock index. The random walk null hypothesis cannot be rejected for longer lag lengths under the assumption of homoscedasticity.

Table 2—Variance Ratios of Chinese Stock Indexes

Lag	Variance Ratio	Homoscedasticity $Z(q)$	Heteroscedasticity $Z^*(q)$
Panel A: Shanghai Index of Class A Shares			
2	1.0562	3.3568	1.6807
4	1.1582	2.6990	2.2772
6	1.2313	2.2607	2.4330
8	1.2698	1.8417	2.3860
10	1.2890	1.5138	2.2751
12	1.2968	1.2612	2.1447
14	1.3040	1.0864	2.0551
16	1.3189	0.9831	2.0423
18	1.3410	0.9241	2.0876
20	1.3673	0.8882	2.1649
22	1.2448	0.5343	1.3953
24	1.4005	0.7967	2.2164
Panel B: Shenzhen Index of Class A Shares			
2	1.0587	3.4593	1.5516
4	1.1420	2.3914	2.0903
6	1.2314	2.2322	2.6512
8	1.2950	1.9876	2.9010
10	1.3417	1.7671	3.0296
12	1.3713	1.5574	3.0476
14	1.4034	1.4230	3.1156
16	1.4371	1.3302	3.2114
18	1.4717	1.2619	3.3214
20	1.5080	1.2124	3.4462
22	1.5332	1.1489	3.4986
24	1.5541	1.0879	3.5256
Panel C: Shanghai Index of Class B Shares			
2	1.1631	9.3218	5.2767
4	1.2647	4.3230	4.7050
6	1.3287	3.0747	4.4720
8	1.3693	2.4127	4.2605
10	1.4033	2.0222	4.1463
12	1.4463	1.8150	4.2029
14	1.4888	1.6718	4.2908
16	1.5269	1.5545	4.3617
18	1.3589	0.9311	2.8258
20	1.5983	1.3848	4.5078
22	1.6326	1.3216	4.5832
24	1.6552	1.2473	4.5835

This differs from the findings for the Malaysian stock market, wherein Lai et al. (2003) reject the random walk null hypothesis under the assumption of homoscedasticity at a 1 percent level of significance for all lag lengths up to and including 24 days. In the case of the Chinese markets, the null hypothesis of random walk is rejected for all lag lengths when we employ the $z^*(q)$ statistic which is robust to heteroscedasticity, suggesting that heteroscedasticity of the error terms is responsible for the apparent randomness in the data for longer lag lengths.

Table 2 (continued)—Variance Ratios of Chinese Stock Indexes

Lag	Variance Ratio	Homoscedasticity $Z(q)$	Heteroscedasticity $Z^*(q)$
Panel D: Shenzhen Index of Class B shares			
2	1.1368	6.5531	3.4793
4	1.2690	3.6823	3.7644
6	1.3967	3.1096	4.2618
8	1.4869	2.6657	4.4559
10	1.5662	2.3795	4.6281
12	1.6302	2.1481	4.7148
14	1.6841	1.9607	4.7575
16	1.7300	1.8049	4.7736
18	1.5405	1.1751	3.3520
20	1.7860	1.5244	4.6531
22	1.8010	1.4024	4.5518
24	1.8015	1.2787	4.3912

Note: This table reports variance ratio test results for lag lengths ranging from two days to 24 days for daily returns

Panels (A) through (D) of Table 3 give details of the forecasting performance of the naïve and ARIMA models for out-of-sample forecasts of one-week ahead prices for the index of both class A and class B shares traded on the Shanghai and Shenzhen stock exchanges. The naïve model presumes that prices follow a random walk model, whereas the ARIMA model assumes that there is autocorrelation in the data and uses an iterative approach to derive the best-fit forecasting model. If the random walk model does indeed prevail, then the ARIMA model should fare no better at forecasting than the naïve model. As is obvious from each of Panels (A) through (D) of Table 3, the naïve model consistently has a higher forecasting error as compared to the ARIMA model. This is true for both class A and class B indexes and is also true for both Shanghai and Shenzhen exchanges. These results support our previous findings from the variance ratio test that the Chinese stock market is autocorrelated over short lag lengths and does not appear to follow a random walk process.

Finally, in Tables 4, 5, and 6, we review the results for the three technical trading rules as applied to all class A and class B shares trading in both the Shanghai or Shenzhen exchanges. Using the buy trade entry and exit prices for a given stock as dictated by our trading rule, we add a 0.5 percent transaction fee to the purchase price and subtract it from the sale price to calculate the geometric average daily return for each buy trade for a given stock. Next, we compute the arithmetic average daily return across all buy trades for that stock over the entire sample period. This procedure is repeated individually for each class A (class B) stock trading in the Shanghai (Shenzhen) exchange and the results are averaged across all stocks to compute the average daily return for the buy signals generated by the trading rule in question. Next, using daily price differences for a given stock, we compute the daily return and the arithmetic average of daily returns across the entire holding period to calculate the overall average daily return for the buy-and-hold strategy for that stock.

Table 3—Forecasting Performance of Alternative Models

Days Ahead	Naïve Model			ARIMA Model			Naïve – ARIMA		
	RMSE	MAE	Theil's U	RMSE	MAE	Theil's U	RMSE	MAE	Theil's U
Panel A: Shanghai Index of Class A Shares									
1	0.04	0.04	3.14	0.01	0.01	1.17	0.03	0.03	1.97
2	0.03	0.03	3.30	0.01	0.01	1.17	0.02	0.02	2.13
3	0.02	0.02	2.89	0.01	0.01	1.17	0.01	0.01	1.72
4	0.02	0.02	2.74	0.01	0.01	1.11	0.01	0.01	1.62
5	0.02	0.02	1.80	0.01	0.01	1.02	0.01	0.01	0.78
Panel B: Shenzhen Index of Class A Shares									
1	0.04	0.04	3.03	0.01	0.01	1.07	0.03	0.03	1.96
2	0.03	0.03	3.14	0.01	0.01	1.05	0.02	0.02	2.09
3	0.03	0.02	3.15	0.01	0.01	1.05	0.02	0.01	2.10
4	0.02	0.02	3.09	0.01	0.01	1.04	0.01	0.01	2.05
5	0.02	0.02	1.81	0.01	0.01	0.99	0.01	0.01	0.82
Panel C: Shanghai Index of Class B Shares									
1	0.02	0.02	1.01	0.02	0.02	1.01	0.00	0.00	-0.01
2	0.04	0.04	1.52	0.03	0.03	1.02	0.01	0.01	0.50
3	0.04	0.03	1.76	0.02	0.02	1.02	0.02	0.02	0.74
4	0.03	0.03	1.75	0.02	0.01	1.02	0.01	0.01	0.73
5	0.03	0.02	1.71	0.02	0.01	1.02	0.01	0.01	0.70
Panel D: Shenzhen Index of Class B Shares									
1	0.03	0.03	1.29	0.03	0.03	1.06	0.01	0.01	0.23
2	0.03	0.03	1.72	0.02	0.02	1.06	0.01	0.02	0.65
3	0.03	0.03	1.60	0.02	0.02	1.05	0.01	0.01	0.54
4	0.03	0.03	1.66	0.02	0.01	1.05	0.01	0.01	0.60
5	0.02	0.02	1.63	0.02	0.01	1.04	0.01	0.01	0.58

Notes: This table reports the forecasting performance of naïve model and ARIMA model. Forecasting errors are measured in terms of RMSE, MAE, and Theil's U. The column of "Naïve – ARIMA" compares the forecasting errors of the naïve and ARIMA models

In Tables 4, 5, and 6, the "Probability of Success" column measures the overall effectiveness of the rule, given by the number of profitable buy trades to the total number of buy trades generated by the rule. A nonparametric test is used to check whether the probability of success estimate obtained for a given trading rule is significantly different from the null hypothesis of 50 percent or 0.50. We do this by comparing the actual number of successful buy trades generated by a given trading rule with the upper/lower boundary estimates of the number of successful buy trades using the formula suggested by Conover (1980).² Finally, we employ a paired-sam-

² T (lower limit at 1 percent level) = $np - 2.58\sqrt{(np(1-p))}$; T (upper limit at 1 percent level) = $np + 2.58\sqrt{(np(1-p))}$;

T (lower limit at 5 percent level) = $np - 1.96\sqrt{(np(1-p))}$; T (upper limit at 5 percent level) = $np + 1.96\sqrt{(np(1-p))}$;

where: T = estimated number of profitable buy trades; n = number of buy trades; p = null hypothesis probability of successful trades (set to 0.50).

ple t-test to check for the significance of the difference in returns obtained between: (a) a given trading rule and the buy-and-hold strategy for class A (class B) shares traded in a given exchange; and (b) class A and class B shares for a given trading rule.

Table 4—Test Results of Moving Average Rules Applied to Individual Chinese Stocks

Rule	Successful Buy Trades	Buy Trades (N)	Prob. of Success	% Return on Buy Trades	% Return on Buy-and- Hold	Rtn Diff (Rule - Buy & Hold) (T-Stat)	Rtn Diff. (A-B) (T-Stat)
Panel A: Stocks Traded On Shanghai Stock Exchange							
Class A Shares							
5,60,0.01	7,652	13,093	0.58*	0.210	-0.016	0.225 (31.41 [^])	
5,120,0.01	5,402	8,413	0.64*	0.214	-0.016	0.230 (30.72 [^])	
5,180,0.01	4,739	6,568	0.72*	0.255	-0.016	0.271 (30.17 [^])	
20,60,0.01	5,181	9,333	0.56*	0.125	-0.016	0.141 (22.80 [^])	
20,120,0.01	3,511	5,629	0.62*	0.150	-0.016	0.165 (26.19 [^])	
20,180,0.01	2,860	4,146	0.69*	0.170	-0.016	0.186 (28.47 [^])	
Class B Shares							
5,60,0.01	660	1,215	0.54*	0.377	0.062	0.315 (11.07 [^])	-0.167 (5.18 [^])
5,120,0.01	400	688	0.58*	0.266	0.062	0.204 (5.53 [^])	-0.052 (1.53)
5,180,0.01	305	493	0.62*	0.302	0.062	0.240 (5.98 [^])	-0.047 (1.16)
20,60,0.01	426	886	0.48	0.166	0.062	0.104 (6.07 [^])	-0.041 (1.45)
20,120,0.01	276	504	0.55**	0.146	0.062	0.084 (4.28 [^])	0.004 (0.14)
20,180,0.01	190	324	0.59*	0.220	0.062	0.158 (6.28 [^])	-0.049 (1.64)

* : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 1 percent

** : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 5 percent

[^] : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 1 percent

^{^^} : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 5 percent

The results for the contrarian version of the moving average rule are presented below in Panels (A) and (B) of Table 4. The rule consistently generates positive average daily returns on buy trades, even after deducting transaction costs of 0.5 percent. This is true for both class A and class B shares traded in both the Shanghai and Shenzhen markets. The average daily return from the contrarian version of the

moving average trading rule consistently outperforms the average daily return from the buy-and-hold strategy. Moreover, the excess returns generated by the contrarian version of the moving average crossover trading rule over the buy-and-hold strategy are always significant at the 1 percent level for both class A and class B shares and across both exchanges, indicating the effectiveness of each of the trading rules tested. Further, we find that the contrarian version of the moving average rule generates profitable trade signals generally in excess of 55 percent for all rules tested on class A shares and the majority of rules tested on class B shares in both exchanges, almost always rejecting the null hypothesis that the probability of success is 50 percent. Finally, in the Shanghai market, we find that returns for class B shares

Table 4 (continued)—Moving Average Rules Applied to Individual Chinese Stocks

Rule	Successful Buy Trades	Buy Trades (N)	Prob. of Success	% Return on Buy Trades	% Return on Buy-and- Hold	Rtn Diff (Rule - Buy & Hold) (T-Stat)	Rtn Diff. (A-B) (T-Stat)
Panel B: Stocks Traded On Shenzhen Stock Exchange							
Class A Shares							
5,60,0.01	5,908	10,198	0.58*	0.262	0.009	0.253 (18.95 [^])	
5,120,0.01	4,336	6,783	0.64*	0.279	0.009	0.270 (26.91 [^])	
5,180,0.01	3,469	5,081	0.68*	0.280	0.009	0.271 (27.77 [^])	
20,60,0.01	4,118	7,380	0.56*	0.151	0.009	0.142 (14.64 [^])	
20,120,0.01	2,686	4,396	0.61*	0.171	0.009	0.162 (24.71 [^])	
20,180,0.01	2,146	3,235	0.66*	0.192	0.009	0.183 (22.03 [^])	
Class B Shares							
5,60,0.01	703	1,265	0.56*	0.358	0.075	0.283 (9.27 [^])	-0.096 (2.41 ^{^^})
5,120,0.01	411	696	0.59*	0.379	0.075	0.304 (7.04 [^])	-0.099 (2.80 [^])
5,180,0.01	315	482	0.65*	0.443	0.075	0.368 (8.88 [^])	-0.163 (4.78 [^])
20,60,0.01	466	897	0.52	0.175	0.075	0.101 (4.92 [^])	-0.024 (0.76)
20,120,0.01	271	480	0.56*	0.273	0.075	0.199 (4.97 [^])	-0.102 (4.20 [^])
20,180,0.01	185	308	0.60*	0.287	0.075	0.212 (4.83 [^])	-0.095 (3.17 [^])

* : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 1 percent

** : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 5 percent

[^] : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 1 percent

^{^^} : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 5 percent

significantly outperform those for class A shares for just one rule tested. The rest of the differences in favor of class B shares are not significant. In the Shenzhen market, class B shares significantly outperform class A shares for five of the six rules tested.

The results for the contrarian version of the channel breakout rule are presented in Panels (A) and (B) of Table 5. Although the daily returns generated by this rule are always positive, we observe that the daily average returns are generally lower than those generated by the contrarian version of the dual moving average crossover rule. This is true for both class A and class B shares traded in both the Shanghai and Shenzhen markets. We find that the excess returns generated by the contrarian version of the channel breakout rule over the buy-and-hold strategy are significant at the 1 percent level for class A shares across all six rules tested for both Shanghai and Shenzhen exchanges, and for three of the six rules tested for class B shares. Further, we find that the contrarian version of the channel breakout rule generates profitable trade signals generally in excess of 55 percent for class A shares traded in both exchanges, almost always rejecting the null hypothesis that the probability of success is 50 percent. The probability of success is generally not significantly different from 50 percent for class B shares traded in the two exchanges. Finally, in the Shanghai market, we find that returns for class B shares significantly outperform those for class A shares for just one rule tested. The rest of the differences in favor of class B shares are not significant. In the Shenzhen market, class B shares significantly outperform class A shares for one of the six rules tested; class A shares outperform class B shares for two of the rules tested; and the remaining three rules yield insignificant return differences.

The results for the contrarian version of the Bollinger band rule are presented in Panels (A) and (B) of Table 6. We find that the contrarian version of the rule consistently generates positive returns for every lag length tested, and the probability of success is significantly above 55 percent for class A shares and insignificantly above 50 percent for class B shares. Once again, we employ the t-test to check for the equality of the mean returns generated by the contrarian version of the Bollinger band trading rule and the buy-and-hold strategy. The excess returns generated by our trading rule are significant at the 1 percent level for class A shares in both the Shanghai and Shenzhen markets across all rules tested and are generally significant at 1 percent or 5 percent for class B shares traded on both the Shanghai and Shenzhen exchanges, for all lag lengths except 150 days and 180 days. In the Shanghai market, we find that there is no significant difference between returns on class A and class B shares. In the Shenzhen market, we find that returns on class B shares are significantly greater than those for class A shares for just two of the six rules tested.

There is a noteworthy difference between our findings and those of Coutts and Cheung (2000) and Lai et al. (2003), both of whom confirm the profitability of conventional moving average rules for the Hang Seng index and the Kuala Lumpur Stock Exchange Composite Index, respectively. Unlike these researchers, we find

Table 5—Test Results of Channel Breakout Rules Applied to Individual Chinese Stocks

Rule	Successful Buy Trades	Buy Trades (N)	Prob. of Success	% Return on Buy Trades	% Return on Buy-and- Hold	Rtn Diff (Rule - Buy & Hold) (T-Stat)	Rtn Diff. (A-B) (T-Stat)
Panel A: Stocks Traded On Shanghai Stock Exchange							
Class A Shares							
20,0.01	8,119	14,748	0.55*	0.187	-0.016	0.203 (30.00 [^])	
40,0.01	4,262	7,718	0.55*	0.121	-0.016	0.137 (25.91 [^])	
60,0.01	2,996	5,107	0.59*	0.116	-0.016	0.132 (14.31 [^])	
120,0.01	1,701	2,382	0.71*	0.163	-0.016	0.179 (23.06 [^])	
150,0.01	1,120	1,567	0.71*	0.148	-0.016	0.164 (18.83 [^])	
180,0.01	818	1,139	0.72*	0.105	-0.016	0.121 (19.25 [^])	
Class B Shares							
20,0.01	725	1,369	0.53**	0.243	0.062	0.181 (8.63 [^])	-0.056 (2.00 ^{^^})
40,0.01	329	739	0.45	0.157	0.062	0.095 (4.36 [^])	-0.036 (1.46)
60,0.01	239	479	0.50	0.141	0.062	0.079 (3.03 [^])	-0.024 (0.63)
120,0.01	103	194	0.53	0.122	0.062	0.061 (2.31 ^{^^})	0.040 (1.19)
150,0.01	75	144	0.52	0.108	0.062	0.046 (1.70)	0.041 (1.10)
180,0.01	63	121	0.52	0.114	0.062	0.053 (1.44)	-0.009 (0.34)

* : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 1 percent

** : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 5 percent

[^] : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 1 percent

^{^^} : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 5 percent

that the contrarian version of three commonly used technical trading rules generates consistent positive returns in the Chinese stock markets for both class A and class B shares, implying that an application of the conventional rules will generate negative returns consistently. This is true for each of the three rules tested. We offer two explanations for the success of the contrarian rather than the conventional version of the three technical trading rules in the Chinese stock markets. First, the high volatility of the Chinese stock market, much more so than in the more well-established Hong Kong or Malaysian stock markets, could be responsible for the success of contrarian trading strategies that are betting on counter-trend activity to be the norm rather than the exception. Second, while the Chinese stock market does exhibit auto

Table 5 (continued)—Test Results of Channel Breakout Rules Applied to Individual Chinese Stocks

Rule	Successful Buy Trades	Buy Trades (N)	Prob. of Success	% Return on Buy Trades	% Return on Buy-and- Hold	Rtn Diff (Rule - Buy & Hold) (T-Stat)	Rtn Diff. (A-B) (T-Stat)
Panel B: Stocks Traded On Shenzhen Stock Exchange							
Class A Shares							
20,0.01	6,332	11,628	0.54*	0.213	0.009	0.204 (14.55^)	
40,0.01	3,445	6,174	0.56*	0.190	0.009	0.181 (19.35^)	
60,0.01	2,378	4,080	0.58*	0.146	0.009	0.137 (20.85^)	
120,0.01	1,306	1,934	0.68*	0.181	0.009	0.172 (19.77^)	
150,0.01	911	1,353	0.67*	0.169	0.009	0.160 (15.79^)	
180,0.01	669	976	0.69*	0.127	0.009	0.118 (12.49^)	
Class B Shares							
20,0.01	837	1,465	0.57*	0.343	0.075	0.268 (7.21^)	-0.129 (2.86^)
40,0.01	352	705	0.50	0.244	0.075	0.169 (2.97^)	-0.054 (1.62)
60,0.01	205	428	0.48	0.167	0.075	0.092 (2.67^)	-0.020 (0.88)
120,0.01	86	183	0.47	0.134	0.075	0.059 (1.34)	0.048 (1.52)
150,0.01	71	155	0.46	0.062	0.075	-0.012 (0.52)	0.106 (3.23^)
180,0.01	63	138	0.46	0.056	0.075	-0.018 (0.73)	0.071 (2.36^^)

* : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 1 percent

** : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 5 percent

^ : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 1 percent

^^ : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 5 percent

correlation of prices and returns over short time lags, the presence of heteroscedasticity in the data ensures that these autocorrelations are not sustained over longer time lags. As a result, contrarian strategies that rely on short-term trends and price retracements have a better chance of outperforming their conventional long-term trend-following counterparts in the Chinese stock markets. In sum, while our results support our earlier findings of the price behavior of the Chinese stock market, it must be noted that the Chinese market is structurally different from the Malaysian and Hong Kong markets.

Table 6—Test Results of Bollinger Band Rules Applied to Individual Chinese Stocks

Rule	Successful Buy Trades	Buy Trades (N)	Prob. of Success	% Return on Buy Trades	% Return on Buy-and- Hold	Rtn Diff (Rule - Buy & Hold) (T-Stat)	Rtn Diff. (A-B) (T-Stat)
Panel A: Stocks Traded On Shanghai Stock Exchange							
Class A Shares							
20	7,912	14,399	0.55*	0.192	-0.016	0.208 (23.28 [^])	
40	4,110	7,528	0.55*	0.130	-0.016	0.146 (19.96 [^])	
60	2,880	4,992	0.58*	0.126	-0.016	0.142 (15.56 [^])	
120	1,489	2,139	0.70*	0.178	-0.016	0.194 (17.84 [^])	
150	1,019	1,480	0.69*	0.151	-0.016	0.167 (15.53 [^])	
180	776	1,098	0.71*	0.124	-0.016	0.140 (17.70 [^])	
Class B Shares							
20	685	1,304	0.53	0.238	0.062	0.176 (8.72 [^])	-0.046 (1.29)
40	324	713	0.45	0.114	0.062	0.052 (2.26 ^{^^})	0.016 (0.50)
60	242	489	0.49	0.162	0.062	0.100 (3.33 [^])	-0.035 (0.90)
120	103	194	0.53	0.132	0.062	0.070 (2.75 [^])	0.047 (1.02)
150	80	146	0.55	0.123	0.062	0.061 (2.03 ^{^^})	0.028 (0.63)
180	62	117	0.53	0.104	0.062	0.042 (1.29)	0.020 (0.60)

* : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 1 percent

** : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 5 percent

[^] : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 1 percent

^{^^} : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 5 percent

Conclusions

This paper studies the behavior of class A and class B shares traded on the Shanghai and Shenzhen stock exchanges, from the inception of each of these markets through December 2004. We find that the Chinese stock markets are more volatile than their counterparts in either Hong Kong or Malaysia. Moreover, we find that the null hypothesis of random walk or no autocorrelation is rejected for short-term lag lengths under the assumption of homoscedasticity and for all lag lengths after correcting for heteroscedasticity. Consistent with this result, we find that the ARIMA forecasting model generates more accurate forecasts as compared to the naïve model

Table 6 (continued)—Test Results of Bollinger Band Rules Applied to Individual Chinese Stocks

Rule	Successful Buy Trades	Buy Trades (N)	Prob. of Success	% Return on Buy Trades	% Return on Buy-and- Hold	Rtn Diff (Rule - Buy & Hold) (T-Stat)	Rtn Diff. (A-B) (T-Stat)
Panel B: Stocks Traded On Shenzhen Stock Exchange							
Class A Shares							
20	6,226	11,460	0.54*	0.194	0.009	0.185 (18.05 [^])	
40	3,377	6,046	0.56*	0.173	0.009	0.163 (22.71 [^])	
60	2,409	4,062	0.59*	0.154	0.009	0.145 (18.27 [^])	
120	1,233	1,848	0.67*	0.203	0.009	0.194 (19.55 [^])	
150	833	1,278	0.65*	0.163	0.009	0.154 (14.27 [^])	
180	638	962	0.66*	0.141	0.009	0.132 (12.70 [^])	
Class B Shares							
20	782	1,402	0.56*	0.385	0.075	0.310 (6.79 [^])	-0.191 (5.38 [^])
40	354	679	0.52	0.252	0.075	0.177 (2.97 [^])	-0.079 (2.72 [^])
60	213	427	0.50	0.134	0.075	0.060 (2.45 ^{^^})	0.019 (0.74)
120	102	196	0.52	0.148	0.075	0.073 (2.20 ^{^^})	0.056 (1.66)
150	75	146	0.51	0.114	0.075	0.040 (1.09)	0.048 (1.37)
180	72	123	0.59**	0.093	0.075	0.018 (0.55)	0.048 (1.46)

* : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 1 percent

** : indicates that the null hypothesis of Probability of Success = 0.50 is rejected at 5 percent

[^] : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 1 percent

^{^^} : indicates that return differences (either (Rule – Buy & Hold) or (class A – class B)) are significant at 5 percent

that assumes that prices follow a random walk process. Finally, we find significant positive returns on buy trades generated by the contrarian version of the moving average crossover rule, the channel breakout rule, and the Bollinger band trading rule, after accounting for transaction costs of 0.50 percent. This suggests that technical trading rules have a useful role to play in the Chinese stock markets.

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