Technical Analysis and the Stochastic Properties of the Jordanian Stock Market Index Return

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Abstract

This paper investigates the performance of moving average rule in an emerging market context, namely that of the Jordanian stock market. The returns from trading strategies based on various moving average rules are examined. The results show that technical trading rules can help to predict market movements, and that there is some evidence that (short) rules may be profitable after allowing for transactions costs, although there are some caveats on this. Sensitivity analysis of the impact of transaction costs is conducted and standard statistical testing is extended through the use of bootstrap techniques. The conditional returns on buy or sell signals from actual data are compared to the conditional returns from simulated series generated by a range of models (random walk with a drift, AR (1), and GARCH-(M)) and the consistency of the general index series with these processes is then examined.

1. INTRODUCTION

This paper examines the performance of moving average trading rules when these are applied to the Index return on the Jordanian Stock market (ASE) [Amman Stock Exchange]. This form of technical analysis is extremely popular amongst practitioners and has been extensively studied in the academic literature (e.g. Neill (1931), Schabacker (1930), Gartley (1930), Caslow (1966), LeBaron (1990), Brock, Lakonishok and LeBaron (1992), Roberts (1959), Brealey (1969), Fama and Blume (1966) and Jensen and Benington (1970)).[1] Much of this early work focussed on major stock markets such as the NYSM, but more recently there have been several studies of emerging markets. For example, Renter and Leal (1999) examined the potential profit of technical trading strategies among 10 emerging equity markets of Latin American and Asia, technical trading strategies found to be profitable for some markets, others were not. Bessembinder and Chan (1995) found similarly mixed results for Asian stock markets.

One might expect that Technical analysis might well 'work' rather better in emerging markets and there is some evidence that this is in fact the case. Harvey (1995) concluded that the autocorrelation in emerging markets is much higher than in developed markets, hence the profitability of technical trading rules in emerging markets is more likely to produce significant results. (See also Bekaert and Harvey

[1] Whilst some forms of technical analysis can be viewed as 'art' or 'subjective judgement', the advent of computerised trading systems has led to great interest by practitioners in technical trading rules which can be programmed and hence automated - and this motivates the question of whether it is possible to earn abnormal profits by the use of such rules.

(1995) Bekaert and Harvey (1997), Claessens, Dasgupta, and Glen (1995), Campbell (1996), Jochum, Kirchgassner and Platek (1999)).

The aim of the present paper is to add a further case study to this developing strand in the literature to examine to what extent the ASE behaves in similar ways to these other markets.[2] Of course, many of the earlier studies (such as Brock, Lakonishok and LeBaron (1992)) ignored transaction costs, costs that can be critical when considering the performance of alternative forms of trading rule. For example, Alexander's (1961) study of Technical Analysis suggested many technical strategies could be quite profitable. However, when Alexander (1964) replicated the earlier study, after adjusting for transactions costs, there was only minimal evidence of profitability. For the ASE, over the period under consideration, transactions costs have varied to some extent, and of course there is some variability depending on who effects the trade and how much is traded. In studying the trading rules, we have chosen to conduct a sensitivity analysis regarding these trading costs by examining how the results are affected by assuming 'average', 'upper' and 'lower' bounds to these costs.[3].

Technical analysis is considered one of the original tools of investment analysis, and has been a part of financial practice dating back to the 1800s. It attempts to forecast prices by detecting patterns in stock prices. Technical analysis is used to examine the efficient market hypothesis by investigating predictability of equity returns from past returns. Some studies (e.g. Chopra, Lakonishok, and Ritter (1992) , and Fama and French (1986)) found negative serial correlations in returns, while other studies found negative serial correlations in first lags and positive correlations in longer lags (e.g. Jegadeesh (1990)). Predictability of stock returns, manifest in various forms of stock market anomaly (such as the size effect, the turn-of-the-year effect, the weekend effect, earning/price (E/P) effect, and the momentum effect) was viewed in the early

[2] Adding further case studies is also beneficial given that emerging markets by definition have shorter data series in comparison with developed markets.

[3] In the ASE, an individual can access the market directly by incurring a variable (fixed percentage) transaction cost for each contract (unlike many other markets where individuals use an agent and pay a fixed fee. Brokers receive commissions calculated on the basis of the market value of both buying and selling transactions of the security. The lower limit for the commissions is 5.4 JD per thousand and the upper limit is 7.4 JD per thousand (see http://www.ase.com.jo/).

literature as evidence of stock market inefficiency. More recently, the concept of market efficiency has been increasingly refined, and other explanations developed (for example, time-varying equilibrium returns, non-linear generating processes (see Neftci (1991), Hsieh (1991), Hsieh (1995), Antoniou, Ergul, and Holmes (1997), and Brorsen and Yang (1994)).

Whilst early studies often found Technical analysis to be ineffective, much of the later work has found some value in it. For example, the Fama and Blume (1966) study of the Dow 30 in the late 1950s found no profits even for the best rule after adjusting for transaction costs whilst the later study by Sweeney (1988), based on the same sample of stocks but for a later period, concluded that mechanical trading rules did have profit potential. Recent work has often found that technical analysis can be an effective means for extracting information from market prices (see for example Pruitt and White (1988), Neftci (1991), Brock, Lakonishok and LeBaron (1992), Neely, Weller, and Dittmar (1997), Neely and Weller (1999), Chang and Osler (1994), and Osler and Chang (1995).

The first object of the paper is to study, in this emerging market, the extent to which alternative moving average trading rules forecast future prices and hence can be profitable. The results of this part of the study generally suggest that technical analysis helps predict stock price changes in the ASE, with the returns during buy periods being larger than returns during sell periods. However, after accounting for transaction costs, taking the moving average rules as a whole (averaging across all the rules), they do not yield significant profit. On the other hand, the average performance of the trading rules actually masks weak performance by ‘long rules’ and superior performance for particular ‘short rules’, which do appear to be profitable. However, these results are based on test statistics which may be unreliable in the face of non-normality of the underlying return distribution. The second objective of the paper is to take some account of this by studying the performance of the trading rules under alternative specifications for the underlying generating process (namely, random walk, AR1, GARCH-M). In each case, the model is fitted to the original data – and the residuals from that model are used in a bootstrap methodology as developed by Efron (1979), Freedman and Peters (1984), Efron and Tibshirami (1986), and Brock, Lakonishok and Lebaron (1992). The bootstrap technique can be used to generate trading rule returns for any given model of the underlying generating process. The comparison between returns from simulated series and those for the actual series reveals that actual trading profits are *not* consistent with those that would be generated using a random walk or AR(1) model (i.e. in both cases, average returns from the trading rules lie in the tails of the simulated distribution), but *are* consistent for most (but not all) trading rules with a GARCH-M model (there is inconsistency for some 'short rules' for 'Buy' strategies). Across all the rules, the GARCH-M model performs well in terms of forecast volatility.

The remainder of the paper is structured as follows: Section 2 describes the data and technical trading rules; Section 3 gives empirical results obtained from applying trading rules; Section 4 describes the bootstrap methodology; Section 5 gives empirical results obtained from bootstrap simulations, and Section 6 concludes by summarising the main findings.

2. DATA AND TECHNICAL TRADING RULES

The Amman Stock Market Index:

The data series used is the daily General index of Amman stock market from 1/1/1992 to 30/7/2001. The period of the study commences at 1/1/1992 because this is the date at which the Amman Stock Exchange (ASE) changed the way of calculation for the Price Index (from unweighted to market capitalization weighted). A base value of 100 points on December 31st, 1991 was stipulated for the new Weighted Price Index[4].

The ASE indices are calculated using the latest closing prices and published on a daily basis. It is composed of 60 companies listed on the 'Regular Market', the selection of these companies being based on the following five criteria which represent the companies' size and liquidity: (i) market capitalization (ii) days traded, (iii) turnover

[4] An anonymous referee raised the question of whether the results were similar if, instead of using the ASE index, the 'S&P' Jordanian Index (as can be obtained from Datastream for example) was used. The ASE index was preferred in this study since this series is longer and more complete (for example, daily data for the S&P Jordanian index before 1995 is not available). However, it is possible to make a comparison by selecting a common set of data points for the two series and running the analysis in parallel for each index. The results were indistinguishable (in terms of parameter estimates, t-statistics etc. and hence conclusions). In what follows, only the results for the longer ASE series are reported.

ratio, (iv) value traded and (v) the number of shares traded. The number of companies included in the index sample was increased to 70 companies at the beginning of August, 2001, hence the choice of end date for the analysis. Within the period, the ASE index has been adjusted to maintain its continuity and to safeguard it from exceptional events. [5]

The Moving Average Trading Rule

The moving average rule is one of the most widely used in technical analysis (see for example de Jong and Penzer(1998), Gencay and Sangos(1997), Liu and Mole(1998), Gencay(1998), Neely and Weller(1999), Ojah and Karemera(1999), Ratner and Leal(1999), Szakmary, Davodson and Schwarz(1999), Couts and Cheung(2000), and Goodacre and Kohn-Speyer(2001)). The standard moving average rule, which utilizes the price line and the moving average of price, generates buy/sell signals is well explained in Gartley (1935) as follows:

> "In an uptrend, long commitments are retained as long as the price trend remains above the moving averages. Thus, when the price trend reaches a top, and turns downward, the downside penetration of the moving average is regarded as a sell signal…. Similarly, in a downtrend, short positions are held as long as the price trend remains

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[5] The index is calculated using the Paasche method. The general formula for the index (t) is:

$Index\ (t) = (M_t/B_t)*100$

$B_t = B_{t-1}*(M_t/M_{ad})$

$M_{ad} = M_t - I_t - N_{t+} + Q_{t-1}$

where,

Index (t) : Index at time t

B_t : base value of Index

M_t : market capitalization of constituents at time t (the sum of the market capitalization of all stocks included in the index)

M_{ad} : adjusted market capitalization at time t. The adjustments are done for new issues of shares, and the addition or deletion of constituents

I_t : market capitalization of new shares issued by a company included in the index and listed at time t

N_t : market capitalization of the company added to the index at time t

Q_{t-1} : market capitalization of the company at time (t-1) which deleted of the index at time t

The base value B_t is an adjusted base (market capitalization) which is not the real market capitalization at the base period. At 1/1/1992 the Index = 100 and the market capitalization = base value of the index No adjustment is made, however, in case of a stock split, bonus shares (stock dividend) and a decrease in paid-in capital, since such corporate actions do not affect the current market capitalization. Thus, adjustments are done for any changes in index constituents or any corporate action affecting the market capitalization on index stocks. This can be achieved by using the adjustment factor M_{ad}. Without any adjustments, such changes would cause sudden and sharp movements of the index value which would not reflect the market's actual behavior. Non-periodic adjustments are made for stocks whose trading is halted for a long time or permanently.

> below the moving average. Thus, when the price trend reaches a bottom, and turns upward, the upside penetration of the moving average is regarded as a buy signal"

There are numerous variations and modifications that can be applied to this rule. In this study, two moving averages are used to generate trading signals. Buy and sell signals are generated by crossovers of a long moving average (calculated over L days) by a short moving average (S days, where $S < L$). That is, the buying signal is generated when the short-period moving average moves higher than the long-period moving average:

$$\frac{\sum_{s=1}^{S} P_{t-s-1}}{S} > \frac{\sum_{\lambda=1}^{L} P_{t-\lambda-l}}{L} \quad \Rightarrow \quad Buy\, at\ time\ \ t \tag{1}$$

where P_t is the price at time t. Sell signals are generated when the inequality is reversed: that is,

$$\frac{\sum_{s=1}^{S} P_{t-s-1}}{S} < \frac{\sum_{\lambda=1}^{L} P_{t-\lambda-l}}{L} \quad \Rightarrow \quad Sell\, at\ time\ \ t$$

The empirical work examines a range of moving averages for the short and long periods ($S = 1,5$ whilst $L = 2,5,10,25,50,100,150,200$ days). This range covers all the moving average rules typically used in practice; perhaps the most popular of these rules is the 1-200 rule ($S = 1, L = 200$), where the short period is one day and the long period is 200 days (Brock, Lakonishok and Lebaron (1992)). The shorter the period covered by the moving average, the closer it follows the market and the longer the period of the moving average, the more it smooths market fluctuations. Thus for example the rule with $S = 1$ is very responsive, in that whenever the actual return rises above (below) the moving average, the signal is to buy (sell).

3. EMPIRICAL RESULTS: TRADITIONAL TESTS

Summary Statistics

Summary statistics for the ASE index are presented in Table 1, and for comparison purposes, parallel results for the S&P500. The return is calculated as log differences of the index level and thus excludes dividend yields. Non-normality in returns is manifest, as expected. Whilst the average return on the ASE over the time period

1992-2001 is about one third that of the S&P, its variance is somewhat less. This is an interesting observation in its own right; most emerging markets manifest higher volatility than established markets. Kurtosis is comparable, but skewness lies in the opposite direction to that commonly manifest by stock markets. Perhaps the most significant feature is that, in contrast to the S&P500, in the ASE, there is significant first order autocorrelation (the partial autocorrelation coefficient value of 0.26648 is massively significant). This indicates that stock prices in the ASE are to an extent predictable on the basis of past price history. The fall away in the partial autocorrelation coefficients after lag 1 is also suggestive that the underlying generating process for the ASE might be characterised as AR1 (this is studied in section 3 below).

Table 1 here

<u>The moving average rules:</u>

Table 2 shows results for fourteen alternative rules. The rules differ in the length set for the short and long period averages. For example, (5,150) denotes that the short average is 5 days and the long average is 150 days. The entire sample is divided into buy and sell periods, depending on the relative position of the moving averages. This rule imitates a trading strategy where the trader buys when the short moving average penetrates the long from below and stays in the market until the short moving average penetrates the long moving average from above, after which the trader moves out of the market or sells short.

The number of buy and sell signals reported during the sample showed in Table 2 as N (Buy) and N (Sell). The daily mean of buy and sell periods are reported in columns 4 and 5 along with the corresponding ***t_statistic***. The latter examines the difference between the unconditional mean (0.000154 as shown in Table 1) and the conditional mean for buy and sell periods in order to investigate any predictability for the trading rules. The ***t_statistic*** for buys calculated as $\frac{\mu_b - \mu}{(\sigma^2 / N + \sigma^2 / N_b)^{1/2}}$, where μ_b and N_b are the mean return and number of signals for the buys, and μ and N are the unconditional mean and number of observations.[6] The estimated variance for the entire sample is denoted as σ^2. The ***t_statistic for*** sells is calculated similarly by using μ_s and N_s as the mean return and number of signals for the sells instead of μ_b and N_b.

In columns 6 and 7, the fraction of buy and sell returns greater than zero are reported. The last column lists the differences between the mean daily buy and sell returns with corresponding ***t_statistic***, calculated as $\frac{\mu_b - \mu_s}{(\sigma^2 / N_b + \sigma^2 / N_s)^{1/2}}$. These three *t*-statistics can be used to test the null hypotheses that a trading strategy based on (a) buy signals is no different from the unconditional mean, (b) for sell signals, it is no different from the unconditional mean, and (c) for buys-sells, it is no different from the unconditional mean. The point is that, if technical analysis does not have any power to forecast price movements, then the returns on days when the rules emit buy signals should not differ appreciably from returns on days when the rules emit sell signals, and this should show up in insignificant *t*-statistics.

Of course, the *t*-statistics reported in Table 1 are only 'indicative' of statistical significance; the actual distribution of the reported "*t*-statistics" is actually unknown, given the manifest non-normality of the return distribution for the ASE index.[7] A bootstrap methodology can be used to derive empirical distributions for these test statistics. This in itself is not a complete solution of course, since to apply the bootstrap requires assumptions regarding the underlying generating process. In the next section, the relative performance of a range of popular generating processes is examined.

Table 2 here

Table 2 gives results when transaction costs are ignored. As shown in Table 2 the number of buy and sell signals generated are fairly similar for all trading rules. In columns 4 and 5, the buy returns are all positive with an average one-day return of

5. σ^2 is the estimated variance for the entire sample.

0.0006 compared with an unconditional mean of 0.000154. Based on the associated *t*-statistics, four of the fourteen tests reject the null hypothesis that the average buy return equals the unconditional average return at the 1 percent significance level using a two-tailed test. The results are systematic, the shorter the moving average, the more significant the result. In the case of the sell return, all are negative with an average one-day return of -0.0003 (that is, getting out of the market or selling short gives a positive return relative to staying in).

Also four of the fourteen tests reject the null hypothesis that the sell returns are equal the unconditional return. The fraction of buys and sells greater than zero shown in Table 2 represent material differences between buys and sells. Under the null hypothesis, the fraction of positive returns should be the same for both buys and sells. The last column in Table 2 shows that the buy-sell differences are positive and the t-test for seven of the fourteen tests are highly significant, which rejects the null hypothesis of equality of zero. Regarding "Buy>0" and "Sell>0" statistics, the buy fraction is consistently greater than 50 percent, while that for all sells it is consistently less.

Having introduced the results for the case where zero transactions costs are assumed, tables 3-5 below examine how the results are affected by introducing transactions costs. Table 3 deals with 'Buy' returns, Table 4 with 'Sell' returns and Table 5 with 'Buy-Sell' returns. By way of sensitivity analysis, results are reported for the average transaction cost level and the upper and lower limits according to ASE regulations, as well as the zero transaction cost case. In each case, as one would expect, the higher the level of transactions cost assumed, the lower the (absolute) values of the t-statistics' and hence the less statistically significant the results appear to be. There is still some indication that 'buy' returns are statistically significant for short moving average rules – for the (1,5) rule for example, where at average transaction cost level t=2.4 and at the upper transaction cost level, t=2.01. Sell returns are rather less 'significant' but taken together, the 'buy-sell' returns are statistically significant for the (1,5)-(1,25) rules even at the upper transaction cost limit.

[7] In this respect the ASE is no different from most stock market indices; returns feature leptokurtosis and time varying heteroskedasticity.

What conclusions can be drawn from this? Clearly, most of the trading rules do not work, but some of the shorter rules do appear to be profitable, even after taking account of transactions costs (notably the (1,5) rule). It would thus appear that trading rules can be used not only to predict market movements, but to also to effect 'profit improving' trading strategies. However, there are several caveats to weigh against this. Firstly it is worth emphasizing that the results are only 'suggestive' given the '*t*-statistics' do not have a *t*-distribution. Secondly, note that a significant range of moving average rules has been examined, so the possibility of 'data mining' has to be considered. Thirdly, there is the question of to what extent one could actually effect the trading schemes implied under tables 3-5. There are always difficulties associated with trading the 'index' portfolio in practice. Given these observations, it is still possible that the first order autocorrelation observed in Table 1 may not be inconsistent with market efficiency when transaction costs are taken into account. Section 3 below sheds further light on this by examining the trading rules under alternative assumptions regarding the return generating process, using a bootstrap methodology.

Tables 3, 4, 5 here

4. A PARAMETRIC BOOTSTRAP METHODOLOGY

The second objective of the paper is to explore, using the bootstrap methodology, the extent to which the above trading results are consistent with alternative specifications of the underlying price generating process (random walk RW, AR1, and GARCH-M are considered). For stock returns, there are several well-known deviations from normality, stationarity and time-independence, such as leptokurtosis, autocorrelation, and conditional heteroskedasticity (see Table 1). Whilst the 't-statistics' calculated and reported in Tables 2-5 give some indication of statistical significance, the theoretical distribution of the 't-statistic' in these contexts is unknown. The bootstrap is a method for estimating the distribution of an estimator or test statistic by re-sampling the data or a model estimated from the data. It can provide approximations to distributions of statistics, coverage probabilities of confidence intervals, and rejection probabilities of hypothesis tests that are more accurate than the approximations of first-order asymptotic distribution theory. However, whilst the parametric bootstrap provides a useful approach to hypothesis testing in situations where the distribution of standard test statistics is unknown, it is worth mentioning that it is an embedded approach, conditional on the specific functional forms used for modelling the volatility process in this study (that is, in this study RW, AR1 or GARCH-M).

The bootstrap methodology allows the development of tests of significance for the trading rules – and this is the focus in what follows. Thus, the basic idea is to compare the time series properties of a simulated data from a given model with those from the actual data. First the postulated models are estimated and then bootstrap samples are generated. Next the trading rule profits are computed for each of the bootstrap samples and compared with the trading rule profits derived in Section 2 from the actual data. Using this methodology, it is also possible to examine the standard deviations of returns during the buy and sell periods, thus giving an indication of the riskiness of the various strategies.

The bootstrap methodology, which was introduced by Efron (Efron (1979)), requires that the information in the sample is "recycled" according to a specific data-generation process to get the sampling distributions of the statistics of interest. It works as follow: Let $(y_1, y_2, \ldots, y_n)$ be the given sample and let θ be some statistic of interest (e.g. standard deviation, kurtosis, a percentile or whatever). Draw a sample of size n from this sample with replacement and denote the j^{th} bootstrap sample as $B_j = (y_1^*, y_2^*, \ldots, y_n^*)$ where each y_i^* is a random pick from $(y_1, y_2, \ldots, y_n)$. This step is repeated for $j=1,2,\ldots,m$ and $\hat{\theta}_j$ is computed for each of the bootstrap samples B_j. The distribution of $\hat{\theta}_j$ is the estimated bootstrap distribution for the estimator θ. Clearly, the number of bootstraps m is likely to likely to affect the 'tightness' with which the distribution is estimated. Although asymptotic properties are unknown for this, it is possible to get a crude assessment of the extent of convergence by repeating the bootstrap process for different values for m. In what follows, results are reported for m=500 and m=2000. These generally indicate that the choice of m=2000 is 'large enough'.

The focus in what follows is on the extent to which the returns generated by trading rules are above or below those generated for the original series. The bootstrap generates a simulated distribution for the performance measure under the assumed process, and it is then possible to calculate an associated *p*-value, where this is defined as the fraction of simulations on which the return from a given trading rule was greater than that gained on the original historical series. Thus the *p*-value indicates the extent to which the historical realization is likely to have been generated from this particular distribution or not. A small or large *p*-value (less than 5 percent, greater than 95%) indicates that the historical performance lies in one of the tails of the distribution, and that the assumed data generating process is unlikely to have given rise to that series. By contrast, *p*-values closer to 0.5 suggest the assumed generating process cannot be rejected as a description of the underlying generating process**.** As explained in section 1 above, three popular generating processes are examined in what follows.

Random Walk Model:

Using the random walk with drift, bootstrap series are generated by simply scrambling the actual returns (log price difference) of the index. Scrambling procedures generate a new time series of returns by randomly drawing from the actual series with replacement. The scrambled series will have the same unconditional distribution, same average drift in prices, and the same volatility. The returns of the scrambled series are independent and identically distributed. With the simulated return series exponentiated back to a simulated price series (the first observation of the actual price is used as a first observation of simulated price), the trading rules are applied to the simulated price series.

AR(1) Model:

The autoregressive model is the second model for the simulation:

$$r_t = b + \rho r_{r-1} + \varepsilon_t \qquad (2)$$

where r_t is the return on day t and ε_t is independent, identically distributed. The parameters and the residuals are estimated using actual returns of the index. The residuals are then resampled with replacement and used with estimated parameters to generate simulated AR(1) series. Given the observed serial correlation in returns (see table 1), it is of interest to see if an autoregressive process might satisfactorily 'explain' the returns observed under the trading strategy(as shown in Panel A in Table 6, there is a significant first order autocorrelation for the index returns series; ρ = 0.266).

GARCH-M Model:

The GARCH-M model with MA term is:

$$r_t = \alpha + \gamma h_t + b\varepsilon_{t-1} + \varepsilon_t \qquad (3)$$

$$h_t = \alpha_0 + \alpha_1 e^2{}_{t-1} + \beta h_{t-1} \qquad (4)$$

$$\varepsilon_t = h_t^{1/2} z_t \qquad z_t \sim N(0,1) \qquad (5)$$

where the residual (ε_t) is conditionally normally distributed with zero mean and conditional variance (h_t) and its standardized residuals (z_t) is i.i.d. $N(0,1)$. In this model the conditional return is a linear function of the conditional variance, h_t, and past disturbance ε_{t-1}. The conditional variance is a linear function of the square of the last period's error and of the last period's conditional variance. Hence, the expected returns are a function of volatility and past returns, and volatility can change over time. The parameters and the standardized residuals are estimated using actual returns of the index. The standardized residuals are then re-sampled with replacement and used with estimated parameters to generate simulated GARCH-M series. Since only the standardized residuals are re-sampled with replacement, the heteroskedastic structure captured in the GARCH-M model is maintained in simulations. Table (3) presents the results of estimated models, which will be used for comparison with the actual index series.

Table 6 here

Panel B of Table 6 presents the results for the GARCH-M model. It shows that the conditional variance of stock returns is time varying and is autocorrelated (both α_1 and β highly significant). There is no significant relation between the conditional variance and conditional mean but as in the AR(1) model, there is significant positive first order autocorrelation in the series (*b* highly significant).

5. BOOTSTRAP RESULTS

The results of the three model simulations (Random Walk, AR(1) process, GARCH-M process) are displayed in tables 7, 8, and 9. Panel A in these tables presents the results for each trading rule. All the numbers presented are the proportion of the simulated results which are larger than the results for the index series. Buy, Sell and Buy-Sell columns present results for returns, whilst SD Buy and SD Sell columns present the result for standard deviations. Panel B of tables 7-9 give some average results. The first row of Panel B (Fraction>Actual) follows the same format as the results presented in Panel A. The second row (Mean) presents the returns and standard deviations for the Buys, Sells and Buy-Sells, averaged over the 500 and 2000 simulation result in panel A. The third row (Actual) presents the same statistic for the original index series. The *p*-values in panel B of the tables can be viewed as a joint test of the significance of the set of rules as a whole.

Tables 7-9 about here

Random Walk Process:

The number in Table 7 under Buy column in the first row, for rule (1,2) is 1.000; this shows that all of the simulated random walks generated a mean buy return larger than the mean buy return from the original index series. This number can be considered as a simulated "*p*-value". The number 0.000 under the Sell column for rule (1,2) shows that none of the simulated random walks generated mean sell returns larger than the mean sell return from the original index series. The number in the Buy-Sell column (1.000) reports that all of the simulated random walks generated mean buy-sell differences larger than the mean differences for the original series. In the column SD-Buy the reported number is (1.000), showing that all of the standard deviations for the simulated random walks are greater than the standard deviation for the original index series, and the number (1.000) under the SD-Sell column shows that all of the standard deviations for the simulated random walks are greater than the standard deviation for the original index series. It is noticeable that the results for the (1,2) rule are rather different from the following rule results; none of the simulated random walk series for the following three rules generated mean buy returns higher than the mean buy returns from the original index series, and all of the simulated random walk series for the following three rules generated mean sell returns higher than the mean sell returns from the original index series.

In general, the results for the Random Walk process give many *p*-values (fraction of results greater than actual) well into the tails of the distribution for the trading rules under investigation (for buys, sells, and buy-sells) particularly for the (1,*X*) rule for $X \in [1,100]$. This implies that the random walk process can be rejected as a potential generating process. This is hardly surprising, given the observed first order serial correlation (see table 1) in the historical series.[8]

AR(1) Process:

Table 8 repeats the previous results for a simulated AR(1) process utilizing the estimated residuals from the original series. The aim of this test is to detect if the observed positive first order autocorrelation (Table 1) explains the results from the trading rules. Table 7 shows results that generally support the AR(1) as a generating process. Panel B shows that the average Buy return from the simulated AR (1) is 0.05% (simple average across all rules), and the average Sell return is (-) 0.02%. These results are not significantly different from the unconditional return of 0.0154 % for the entire sample. The same observation holds in Panel B for the mean of Buy-Sell return for the simulated series which at 0.00070 is only slightly less than the actual Buy-Sell return (0.00098). In panel A, the *p-values* for all rules – except the (1,2) rule - are all higher than 10% (and less than 90%). On the basis of these rules one would not reject the null hypothesis that the AR(1) process is consistent with the data generating process of stock index return. However, the (1,2) rule has a significant *p-value*, so this casts some doubt over the validity of process. Naturally, the *p-values* for the simulated AR(1) process are in general less significant than those for the simulated RW process, suggesting that 'AR(1) type' effects do play a role in the process generating the original results.

[8] In Panel B of Table 7, the first row shows insignificant differences in the average p-values (averages taken across all the rules). However, this masks the fact that whilst the (5,X) rules are generally not significant (p-values greater than 5%), the (1,X) rules generally are.

GARCH-M Process:

Table 9 repeats the previous results for a simulated GARCH-M process utilizing the estimated standardized residuals from the original series. Both conditional means and variances are allowed to change over time in this model. A changing conditional mean can potentially explain some of the differences between Buy and Sell returns. As shown in panel B, GARCH-M generates no significant differences. For example, around 20% of the simulations generated Buy-Sell returns larger than Buys-Sells generated by original data. For volatility results, given that the focal point of GARCH models is to predict volatility, Panel B shows the GARCH-M average standard deviation for Buys to be 0.55% which should be compared with 0.52% for the original data with an associated *p-value* of 56% showing the lack of significance. The average standard deviation for Sells for the replications is 0.46% and for the original data is 0.44% which again are close, with a *p-value* of 58%. In panel A, none of the *p-values* show significance with the exception of (1,2) and (1,5) rules for Sells (an again, only just at 5% for a one tailed test, or at 10% for a two tailed test). Overall then, the GARCH-M model is performing rather better than the other models, with only the short rules and furthermore, only for Sells, showing some 'discrepancy'. The model also works well across all rules in terms of predicting volatility .

6 CONCLUSIONS

The first object of the paper was to study, in this emerging market, the extent to which alternative moving average trading rules help to forecast market movements and the extent to which these might be profitable. The results of this part of the study suggest that technical analysis does help to predict stock price changes in the ASE. This evidence regarding predictive power agrees fairly well with results from other studies conducted in developed and emerging markets. For example, Brock et al.(1992) examined a moving average trading rule for the daily Industrial Average Dow Jones, and found that the buy (sell) signals generate returns which are higher (or lower) than normal returns. Hudson et al. (1996) also adopted the same technical trading rules as Brock et al.(1992) to UK stock prices, and likewise found predictive ability for technical trading rules. Furthermore, the results agree with studies performed in other emerging markets; for example, Bessembinder and Chan (1995), Ratner and Leal [1999] both found that simple trading rules can have forecast ability.

In common with previous studies, it was found that the returns during buy periods are larger than returns during sell periods. Under the assumption of zero transactions costs, moving average rules (1,2), (1,5), (1,10), (1,25), (1,50), (5,10), and (5,25) all appeared to have significant predictive power. However, after account of transactions costs was taken, despite predictive power, the ability to earn a significant trading profit was considerably lessened. There was still *some* evidence that *some* short run rules (such as the 1-5 rule) might yield net profit even after allowing for trading costs. Fairly clearly however, the trading rules examined, on the average, do not (most of the rules do not yield significant trading profits). It was suggested that the finding that some (short) rules seem to be profitable net of transactions costs was an indication of potential market inefficiency, but there are some caveats to such a conclusion – firstly because the test statistics cannot be relied upon to have the standard *t*-distribution (because of non-normality of the index return), secondly, because of data mining considerations, and thirdly because, for the trading strategy based on a moving average rule to be profitable, is does require that the index portfolio needs to be traded, and there may be practical difficulties associated with doing this (which will depend on market micro-structure). Given these considerations, the results can be viewed as fairly consistent with those found in the recent literature (namely that moving average rules do help to predict market movements, but that it may be hard to profitably exploit the trading strategy in practice).

The second objective of the paper was to study the performance of the moving average trading rules under alternative specifications for the underlying generating process (namely, random walk, AR1, GARCH-M). In each case, the model was fitted to the original data and the residuals from that model used as the basis for a bootstrap study. The bootstrap technique was used to generate trading rule returns for each given model for the underlying generating process. The comparison between returns generated by the bootstrap and those for the actual series reveals that actual trading profits are not consistent with those that could be generated by the random walk or AR(1) processes. There was more evidence in favour of a GARCH-M process, although still some evidence of inconsistent performance for short moving average rules for Sells (but not for Buys). Overall, increasing ‘flexibility’ in moving from RW to AR(1) to GARCH-M increases substantially the consistency (in terms of *p-values*) of actual historical returns with estimated return distributions.

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Table 1
Summary Statistic for Daily Returns

Returns are measured as log differences of the level of the index. AC is the estimated autocorrelation and PAC is the estimated partial autocorrelation at lags 1,2,3,4and 5.Q-Stat is the Ljung-Box Q-statistic

	ASE Index	S&P Index
Mean	0.000154	0.000427
Standard Deviation	0.006831	0.009639
Sample Variance	0.000047	0.000093
Kurtosis	5.796881	5.294313
Skewness	0.422431	-0.272796
Range	0.090551	0.121014
Minimum	-0.043102	-0.071127
Maximum	0.047449	0.049887
Observations	2345	2345

ASE Index	AC	PAC	Q-Stat	Prob
1	0.266418	0.266418	166.6577	3.97E-38
2	0.012861	-0.06256	167.0463	5.33E-37
3	-0.02	-0.00754	167.9863	3.46E-36
4	-0.02805	-0.02119	169.8358	1.13E-35
5	-0.01864	-0.0068	170.653	5.29E-35

S&P Index	AC	PAC	Q-Stat	Prob
1	-0.005	-0.005	0.0717	0.789
2	-0.03	-0.03	2.35	0.309
3	-0.053	-0.053	9.2809	0.026
4	-0.007	-0.008	9.3969	0.052
5	-0.019	-0.023	10.334	0.066

Table 2
Test Results for the Trading Rules in the Absence of Transactions Costs

Results for daily prices from 1992-2000. Rules are identified as (short, long) where short is the short moving average and long is the long moving average. N(Buy) and N(Sell) are the number of buy and sell signals reported during the sample. Bold numbers are standard *t*-ratios testing the difference of the mean buy and mean sell from the unconditional mean, and buy-sell from zero. Buy >0 and Sell >0 are the fraction of buy and sell returns greater than zero. The last row reports the averages across all 14 rules.

Rule	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
(1, 2)	1102	1239	0.0018	-0.0013	0.6758	0.3388	0.0032
t-statistic			**(6.74)****	**(-6.19)****			**(11.20)****
(1, 5)	1093	1248	0.0014	-0.0009	0.6349	0.3874	0.0023
t-statistic			**(4.93)****	**(-4.59)****			**(8.25)****
(1, 10)	1079	1257	0.0010	-0.0006	0.5994	0.4276	0.0016
t-statistic			**(3.45)****	**(-3.20)****			**(5.76)****
(1, 25)	1165	1156	0.0007	-0.0005	0.5739	0.4475	0.0012
t-statistic			**(2.39)****	**(-2.47)****			**(4.21)****
(1, 50)	1152	1144	0.0006	-0.0003	0.5597	0.4672	0.0009
t-statistic			**(1.76)**	**(-1.80)**			**(3.08)****
(1, 100)	1141	1105	0.0004	-0.0001	0.5407	0.4848	0.0005
t-statistic			**(0.99)**	**(-1.14)**			**(1.84)**
(1, 150)	1185	1011	0.0004	-0.0002	0.5389	0.4826	0.0005
t-statistic			**(0.95)**	**(-1.18)**			**(1.83)**
(1, 200)	1150	996	0.0004	-0.0002	0.5356	0.4773	0.0006
t-statistic			**(0.82)**	**(-1.35)**			**(1.86)**
(5, 10)	1078	1257	0.0006	-0.0002	0.5585	0.4715	0.0008
t-statistic			**(1.74)**	**(-1.66)**			**(2.95)****
(5, 25)	1153	1168	0.0005	-0.0002	0.5514	0.4772	0.0007
t-statistic			**(1.40)**	**(-1.46)**			**(2.48)****
(5, 50)	1153	1143	0.0004	-0.0001	0.5387	0.4918	0.0004
t-statistic			**(0.88)**	**(-0.92)**			**(1.56)**
(5, 100)	1131	1115	0.0003	0.0000	0.5291	0.4991	0.0003
t-statistic			**(0.52)**	**(-0.65)**			**(1.01)**
(5, 150)	1185	1011	0.0003	0.0000	0.5274	0.4987	0.0003
t-statistic			**(0.46)**	**(-0.64)**			**(0.95)**
(5, 200)	1151	995	0.0003	-0.0001	0.5258	0.4911	0.0003
t-statistic			**(0.40)**	**(-0.89)**			**(1.12)**
Average			0.0006	-0.0003			0.0010

* denotes p<0.05, ** denotes $p < 0.01$.

Table 3: The Buy Return before and after deducting transaction costs. Three percentages of transaction costs are used. The lower limit, the average and the upper limit (lower and upper limits defined by ASE regulations).

	Buy Return				Buy and Hold Return
Transaction Cost:	**Zero TC 0**	**Lower limit 0.0054**	**Average limit 0.0064**	**Upper limit 0.0074**	
Rule					
(1, 2)	0.00184	0.00077	0.00057	0.00038	0.00015
t-statistic	**(6.75)****	**(2.48)***	**(1.68)**	**(0.89)**	
(1, 5)	0.00139	0.00085	0.00076	0.00066	0.00015
t-statistic	**(4.94)****	**(2.80)****	**(2.40)***	**(2.01)***	
(1, 10)	0.00102	0.00065	0.00059	0.00052	0.00015
t-statistic	**(3.46)****	**(1.99)***	**(1.72)**	**(1.45)**	
(1, 25)	0.00074	0.00054	0.00050	0.00047	0.00015
t-statistic	**(2.40)***	**(1.58)**	**(1.43)**	**(1.27)**	
(1, 50)	0.00059	0.00046	0.00043	0.00041	0.00015
t-statistic	**(1.76)**	**(1.23)**	**(1.13)**	**(1.03)**	
(1, 100)	0.00040	0.00031	0.00029	0.00027	0.00015
t-statistic	**(1.00)**	**(0.63)**	**(0.56)**	**(0.49)**	
(1, 150)	0.00039	0.00031	0.00030	0.00028	0.00015
t-statistic	**(0.96)**	**(0.64)**	**(0.59)**	**(0.53)**	
(1, 200)	0.00036	0.00030	0.00029	0.00028	0.00015
t-statistic	**(0.82)**	**(0.60)**	**(0.55)**	**(0.51)**	
(5, 10)	0.00059	0.00032	0.00027	0.00022	0.00015
t-statistic	**(1.75)**	**(0.66)**	**(0.45)**	**(0.25)**	
(5, 25)	0.00050	0.00037	0.00035	0.00033	0.00015
t-statistic	**(1.41)**	**(0.89)**	**(0.80)**	**(0.70)**	
(5, 50)	0.00037	0.00029	0.00028	0.00026	0.00015
t-statistic	**(0.89)**	**(0.56)**	**(0.50)**	**(0.43)**	
(5, 100)	0.00028	0.00023	0.00022	0.00021	0.00015
t-statistic	**(0.52)**	**(0.31)**	**(0.27)**	**(0.23)**	
(5, 150)	0.00027	0.00022	0.00022	0.00021	0.00015
t-statistic	**(0.46)**	**(0.28)**	**(0.25)**	**(0.22)**	
(5, 200)	0.00025	0.00022	0.00022	0.00021	0.00015
t-statistic	**(0.41)**	**(0.28)**	**(0.25)**	**(0.23)**	

Table 4: The Sell Return before and after deducting the transaction costs. Three percentages of transaction costs are used. The lower limit (according to ASE regulations), the average and the upper limit.

	Sell Return				Buy and Hold Return
Transaction Cost:	**Zero TC 0**	**Lower limit 0.0054**	**Average limit 0.0064**	**Upper limit 0.0074**	
Rule					
(1, 2)	-0.00133	-0.00027	-0.00007	0.00013	0.00015
t-statistic	**(-6.20)****	**(-1.75)**	**(-0.93)**	**(-0.11)**	
(1, 5)	-0.00095	-0.00041	-0.00031	-0.00021	0.00015
t-statistic	**(-4.66)****	**(-2.36)***	**(-1.95)**	**(-1.54)**	
(1, 10)	-0.00061	-0.00024	-0.00018	-0.00011	0.00015
t-statistic	**(-3.21)****	**(-1.66)**	**(-1.38)**	**(-1.09)**	
(1, 25)	-0.00045	-0.00025	-0.00022	-0.00018	0.00015
t-statistic	**(-2.47)***	**(-1.66)**	**(-1.51)**	**(-1.36)**	
(1, 50)	-0.00029	-0.00016	-0.00014	-0.00011	0.00015
t-statistic	**(-1.81)**	**(-1.27)**	**(-1.18)**	**(-1.08)**	
(1, 100)	-0.00013	-0.00004	-0.00002	-0.00001	0.00015
t-statistic	**(-1.15)**	**(-0.78)**	**(-0.71)**	**(-0.64)**	
(1, 150)	-0.00015	-0.00008	-0.00006	-0.00005	0.00015
t-statistic	**(-1.19)**	**(-0.89)**	**(-0.84)**	**(-0.78)**	
(1, 200)	-0.00020	-0.00014	-0.00013	-0.00012	0.00015
t-statistic	**(-1.35)**	**(-1.14)**	**(-1.10)**	**(-1.06)**	
(5, 10)	-0.00024	0.00003	0.00008	0.00013	0.00015
t-statistic	**(-1.67)**	**(-0.52)**	**(-0.31)**	**(-0.10)**	
(5, 25)	-0.00020	-0.00008	-0.00005	-0.00003	0.00015
t-statistic	**(-1.46)**	**(-0.94)**	**(-0.85)**	**(-0.75)**	
(5, 50)	-0.00007	0.00001	0.00002	0.00004	0.00015
t-statistic	**(-0.93)**	**(-0.66)**	**(-0.54)**	**(-0.48)**	
(5, 100)	-0.00001	0.00004	0.00005	0.00006	0.00015
t-statistic	**(-0.65)**	**(-0.44)**	**(-0.40)**	**(-0.36)**	
(5, 150)	-0.00001	0.00003	0.00004	0.00005	0.00015
t-statistic	**(-0.64)**	**(-0.47)**	**(-0.44)**	**(-0.41)**	
(5, 200)	-0.00008	-0.00005	-0.00004	-0.00003	0.00015
t-statistic	**(-0.90)**	**(-0.78)**	**(-0.75)**	**(-0.73)**	

Table 5: The Buy –Sell Return before and after deducting the transaction costs. Three percentages of transaction costs are used. The lower limit (according to ASE regulations), the average and the upper limit.

	Buy-Sell Return				Buy and Hold Return
Transaction Cost:	**Zero TC 0**	**Lower limit 0.0054**	**Average limit 0.0064**	**Upper limit 0.0074**	
Rule					
(1, 2)	0.00317	0.00104	0.00064	0.00025	0.00015
t-statistic	**(11.21)****	**(3.67)****	**(2.27)***	**(0.88)**	
(1, 5)	0.00233	0.00127	0.00107	0.00087	0.00015
t-statistic	**(8.25)****	**(4.47)****	**(3.78)****	**(3.08)****	
(1, 10)	0.00163	0.00090	0.00076	0.00062	0.00015
t-statistic	**(5.76)****	**(3.16)****	**(2.68)****	**(2.20)***	
(1, 25)	0.00119	0.00079	0.00072	0.00064	0.00015
t-statistic	**(4.21)****	**(2.80)****	**(2.54)***	**(2.27)***	
(1, 50)	0.00088	0.00062	0.00057	0.00052	0.00015
t-statistic	**(3.08)****	**(2.16)***	**(1.99)***	**(1.82)**	
(1, 100)	0.00053	0.00035	0.00031	0.00028	0.00015
t-statistic	**(1.85)**	**(1.21)**	**(1.09)**	**(0.97)**	
(1, 150)	0.00054	0.00039	0.00036	0.00033	0.00015
t-statistic	**(1.84)**	**(1.32)**	**(1.22)**	**(1.13)**	
(1, 200)	0.00055	0.00044	0.00042	0.00040	0.00015
t-statistic	**(1.87)**	**(1.49)**	**(1.42)**	**(1.35)**	
(5, 10)	0.00084	0.00029	0.00019	0.00009	0.00015
t-statistic	**(2.95)****	**(1.02)**	**(0.66)**	**(0.30)**	
(5, 25)	0.00070	0.00045	0.00040	0.00036	0.00015
t-statistic	**(2.48)***	**(1.59)**	**(1.42)**	**(1.26)**	
(5, 50)	0.00045	0.00028	0.00026	0.00023	0.00015
t-statistic	**(1.56)**	**(1.00)**	**(0.89)**	**(0.79)**	
(5, 100)	0.00029	0.00018	0.00017	0.00015	0.00015
t-statistic	**(1.01)**	**(0.64)**	**(0.57)**	**(0.51)**	
(5, 150)	0.00028	0.00019	0.00017	0.00016	0.00015
t-statistic	**(0.95)**	**(0.65)**	**(0.60)**	**(0.54)**	
(5, 200)	0.00033	0.00027	0.00026	0.00024	0.00015
t-statistic	**(1.12)**	**(0.91)**	**(0.87)**	**(0.83)**	

Table 6

Parameter estimates for AR(1), and GARCH Models

PanelA:AR(1) Parameter Estimates

$$r_t = b + \rho r_{t-1} + \varepsilon_t$$

	b	***ρ***
Estimate:	0.00011	0.26642
t-statistic:	(0.8220)	(13.3769)**
Prob. :	0.411	0

Panel B:GARCH-M Parameter Estimates

$$r_t = \alpha + \gamma h_t + b\varepsilon_{t-1} + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 e^2{}_{t-1} + \beta h_{t-1}$$
$$\varepsilon_t = h_t^{1/2} z_t$$

$z_t \sim N(0,1)$

	α_0	α_1	β	α	γ	***b***
Estimate:	3.44E-06	0.21851	0.711161	-4E-04	8.933	0.25744
t-statistic:	(10.4004)**	(12.5907)**	(41.6014)**	(-1.915)	(1.556)	(11.1528)**
Prob. :	8.50E-25	3.20E-35	1.27E-283	0.0557	0.12	3.50E-28

Table 7
Simulation Tests from Random Walk Bootstrap for 500 and 2000 Replications

Panel A						
			Results (Fraction>Actual)			
Rule		Buy	SD Buy	Sell	SD Sell	Buy-Sell
(1, 2)	500bootstrap	1	1	0	1	1
	2000bootstrap	**1**	**1**	**0**	**1**	**1**
(1, 5)	500bootstrap	0	0.212	1	0.924	0
	2000bootstrap	**0**	**0.179**	**1**	**0.91**	**0**
(1, 10)	500bootstrap	0	0.384	1	0.662	0
	2000bootstrap	**0**	**0.3775**	**1**	**0.6755**	**0**
(1, 25)	500bootstrap	0	0.35	1	0.618	0
	2000bootstrap	**0.0015**	**0.349**	**0.9995**	**0.6305**	**0**
(1, 50)	500bootstrap	0.006	0.49	0.986	0.426	0
	2000bootstrap	**0.006**	**0.4945**	**0.991**	**0.4275**	**0.0005**
(1, 100)	500bootstrap	0.058	0.384	0.924	0.62	0.022
	2000bootstrap	**0.068**	**0.395**	**0.935**	**0.6265**	**0.0195**
(1, 150)	500bootstrap	0.068	0.268	0.944	0.692	0.02
	2000bootstrap	**0.0815**	**0.265**	**0.947**	**0.708**	**0.0225**
(1, 200)	500bootstrap	0.106	0.3	0.962	0.63	0.016
	2000bootstrap	**0.119**	**0.3075**	**0.9585**	**0.632**	**0.0225**
(5, 10)	500bootstrap	0.014	0.474	0.978	0.504	0.002
	2000bootstrap	**0.01**	**0.463**	**0.9825**	**0.54**	**0.0005**
(5, 25)	500bootstrap	0.034	0.588	0.974	0.378	0.004
	2000bootstrap	**0.0345**	**0.553**	**0.968**	**0.399**	**0.006**
(5, 50)	500bootstrap	0.1	0.592	0.882	0.322	0.05
	2000bootstrap	**0.1205**	**0.5605**	**0.879**	**0.3465**	**0.044**
(5, 100)	500bootstrap	0.212	0.402	0.828	0.608	0.116
	2000bootstrap	**0.237**	**0.394**	**0.7835**	**0.605**	**0.1325**
(5, 150)	500bootstrap	0.238	0.32	0.802	0.612	0.116
	2000bootstrap	**0.254**	**0.336**	**0.792**	**0.6065**	**0.134**
(5, 200)	500bootstrap	0.258	0.348	0.894	0.584	0.082
	2000bootstrap	**0.2835**	**0.355**	**0.874**	**0.576**	**0.0955**
Panel B						
p-value	500bootstrap	0.149571	0.436571	0.869571	0.612857	0.102
p-value	**2000bootstrap**	**0.15825**	**0.430643**	**0.865**	**0.620214**	**0.105536**
Mean Return	500bootstrap	0.000504	0.005182	-0.00013	0.00465	0.000629
Mean Return	**2000bootstrap**	**0.000503**	**0.005174**	**-0.00013**	**0.004658**	**0.00063**
Actual Mean Return		0.001436	0.005228	-0.0011	0.004282	0.002538

Table 8
Simulation Tests from AR(1) Bootstrap for 500 and 2000 Replications

Rule		Buy	SD Buy	Sell	SD Sell	Buy-Sell
Panel A						
		Results (Fraction>Actual)				
(1, 2)	500bootstrap	0.0300	0.0760	0.9100	0.9380	0.0100
	2000bootstrap	**0.0405**	**0.1205**	**0.8795**	**0.9575**	**0.0165**
(1, 5)	500bootstrap	0.1560	0.2240	0.6740	0.8520	0.1460
	2000bootstrap	**0.1430**	**0.2255**	**0.6795**	**0.8255**	**0.1380**
(1, 10)	500bootstrap	0.2580	0.3660	0.4520	0.6020	0.3500
	2000bootstrap	**0.2890**	**0.3925**	**0.4915**	**0.6125**	**0.3425**
(1, 25)	500bootstrap	0.2780	0.2980	0.6640	0.7000	0.2100
	2000bootstrap	**0.2980**	**0.3405**	**0.6600**	**0.6500**	**0.2450**
(1, 50)	500bootstrap	0.2680	0.4180	0.5980	0.5100	0.2660
	2000bootstrap	**0.3030**	**0.4405**	**0.6175**	**0.4955**	**0.2760**
(1, 100)	500bootstrap	0.4160	0.3040	0.4980	0.7140	0.4460
	2000bootstrap	**0.4465**	**0.3360**	**0.5265**	**0.6870**	**0.4130**
(1, 150)	500bootstrap	0.3360	0.1940	0.6100	0.7920	0.2660
	2000bootstrap	**0.3930**	**0.2025**	**0.6560**	**0.7645**	**0.2775**
(1, 200)	500bootstrap	0.3440	0.2180	0.7440	0.7260	0.1900
	2000bootstrap	**0.3945**	**0.2375**	**0.7680**	**0.7105**	**0.2105**
(5, 10)	500bootstrap	0.2100	0.4660	0.7480	0.5000	0.1500
	2000bootstrap	**0.2010**	**0.4525**	**0.7410**	**0.5300**	**0.1365**
(5, 25)	500bootstrap	0.2200	0.4960	0.7880	0.4460	0.1200
	2000bootstrap	**0.1865**	**0.5135**	**0.8005**	**0.4455**	**0.1100**
(5, 50)	500bootstrap	0.3180	0.4940	0.7000	0.4240	0.2240
	2000bootstrap	**0.2995**	**0.4935**	**0.6720**	**0.4285**	**0.2250**
(5, 100)	500bootstrap	0.4040	0.3380	0.6220	0.6680	0.3140
	2000bootstrap	**0.3765**	**0.3365**	**0.6455**	**0.6865**	**0.2925**
(5, 150)	500bootstrap	0.3980	0.2680	0.6500	0.6660	0.2840
	2000bootstrap	**0.3765**	**0.2730**	**0.6630**	**0.6935**	**0.2690**
(5, 200)	500bootstrap	0.4080	0.2900	0.7680	0.6320	0.2260
	2000bootstrap	**0.3850**	**0.2885**	**0.7560**	**0.6525**	**0.1965**
Panel B						
p-value	500bootstrap	0.2889	0.3179	0.6733	0.6550	0.2287
p-value	**2000bootstrap**	**0.2952**	**0.3324**	**0.6826**	**0.6528**	**0.2249**
Mean Return	500bootstrap	0.0005	0.0050	-0.0002	0.0046	0.0007
Mean Return	**2000bootstrap**	**0.0005**	**0.0050**	**-0.0002**	**0.0046**	**0.0007**
Actual Mean Return		0.0014	0.0052	-0.0011	0.0043	0.0025

Table 9
Simulation Tests from GARCH-M Bootstrap for 500 and 2000 Replications

Panel A						
		Results (Fraction>Actual)				
Rule		Buy	SD Buy	Sell	SD Sell	Buy-Sell
(1, 2)	500bootstrap	0.096	0.536	0.974	0.81	0.022
	2000bootstrap	**0.0895**	**0.506**	**0.97**	**0.787**	**0.0265**
(1, 5)	500bootstrap	0.098	0.63	0.96	0.628	0.026
	2000bootstrap	**0.0955**	**0.608**	**0.9505**	**0.594**	**0.035**
(1, 10)	500bootstrap	0.202	0.69	0.86	0.442	0.102
	2000bootstrap	**0.1915**	**0.6665**	**0.8325**	**0.433**	**0.11**
(1, 25)	500bootstrap	0.27	0.634	0.864	0.488	0.148
	2000bootstrap	**0.2805**	**0.6185**	**0.8475**	**0.464**	**0.1535**
(1, 50)	500bootstrap	0.318	0.646	0.742	0.442	0.222
	2000bootstrap	**0.315**	**0.618**	**0.723**	**0.408**	**0.2315**
(1, 100)	500bootstrap	0.442	0.55	0.568	0.642	0.406
	2000bootstrap	**0.4235**	**0.5305**	**0.5665**	**0.6435**	**0.396**
(1, 150)	500bootstrap	0.39	0.448	0.68	0.78	0.276
	2000bootstrap	**0.3885**	**0.4365**	**0.6775**	**0.7535**	**0.317**
(1, 200)	500bootstrap	0.368	0.44	0.794	0.75	0.2
	2000bootstrap	**0.3855**	**0.433**	**0.782**	**0.7185**	**0.2365**
(5, 10)	500bootstrap	0.184	0.662	0.846	0.428	0.084
	2000bootstrap	**0.1995**	**0.6695**	**0.8535**	**0.4315**	**0.104**
(5, 25)	500bootstrap	0.258	0.642	0.848	0.396	0.138
	2000bootstrap	**0.2625**	**0.673**	**0.8435**	**0.379**	**0.1485**
(5, 50)	500bootstrap	0.324	0.606	0.704	0.424	0.222
	2000bootstrap	**0.3595**	**0.63**	**0.6865**	**0.4015**	**0.2835**
(5, 100)	500bootstrap	0.372	0.486	0.622	0.676	0.32
	2000bootstrap	**0.423**	**0.505**	**0.6205**	**0.667**	**0.349**
(5, 150)	500bootstrap	0.356	0.436	0.636	0.736	0.294
	2000bootstrap	**0.4255**	**0.4515**	**0.64**	**0.7145**	**0.339**
(5, 200)	500bootstrap	0.39	0.42	0.768	0.708	0.238
	2000bootstrap	**0.426**	**0.4465**	**0.7475**	**0.6985**	**0.2715**
Panel B						
p-value	500bootstrap	0.290571	0.559	0.776143	0.596429	0.192714
p-value	**2000bootstrap**	**0.304679**	**0.556607**	**0.767214**	**0.578107**	**0.214393**
Mean Return	500bootstrap	0.000494	0.005582	-0.00016	0.004653	0.00065
Mean Return	**2000bootstrap**	**0.000503**	**0.005544**	**-0.00016**	**0.004634**	**0.000664**
Actual Mean Return		0.001436	0.005228	-0.0011	0.004282	0.002538