Technical Trading Rules and Market Efficiency: Evidence from the Australian Stock Exchange 1980 – 2002

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Abstract

This paper examines the validity of two classes of simple technical trading rules – moving averages and trading range breaks – in the Australian Stock Exchange. We conduct our empirical analysis in two stages. In the first stage, standard *t*-tests are used to compare returns generate by the technical trading rules against those generated by the buy-and-hold equivalent. In the second stage, we employ bootstrap methods to generate empirical distributions of trading returns simulated under four models of stock prices – the random walk with drift, AR(1), GARCH(1,1) and EGARCH(1,1) models. Using daily data from 1 January 1980 to 31 December 2002, we find that technical rules possess some predictive power over the full sample period. However, tests on four non-overlapping sub-samples reveal that the technical rules generate returns in excess of the buy-and-hold equivalent only in the pre-1991 sample period, but then begin to generate negative returns in the sample period post 1991. Results from the second stage tests also indicate that it is possible to reverse the standard test outcome of predictability by addressing non-normality, time-dependence and conditional heteroskedasticity in the data. Overall, our results finds the ASX informationally efficient and that the period post-1991 marks a significant rise in the stock market's efficiency.

Key words: Australian stock market, Technical Trading Rules, Stock Market Efficiency and Bootstrapping.

1.0 Introduction

Technical trading rules are forecasting techniques used typically by the private sector to predict the future directional movement of stock prices by detecting trends and patterns in past prices. Because these techniques were introduced long before the birth of modern financial theory, the general academic community has traditionally doubted the validity of technical trading rules for their lack of theoretical foundations. A more important reason for this perception is that technical trading rules conflict with one basic principle of finance theory – the Efficient Markets Hypothesis (EMH) – which states that future returns cannot be predicted from the information contained in past prices when the asset market is informationally efficient. This contempt of technical trading rules is further fueled by the fact that early research on simple technical rules, such as the ones by Alexander (1964) and Fama and Blume (1966), also yield unprofitable results. Due to these reasons, there was a general lack of interest in the research of technical trading rules within the academic community.

More recently, however, there is a change from the traditional perception of technical trading rules after a study by Brock, Lakonishok and LeBaron (1992) presented evidence that abnormal returns can be obtained by applying simple technical trading rules to the Dow Jones Industrial Averages (DJIA). Because these results were controversial to traditional views, Brock, Lakonishok and LeBaron (1992) spawned several other studies that examine if similar results may also be obtained using different data. Thus far, the literature on technical trading rules includes studies on data obtained from the United States, the United Kingdom and other European Union countries, Asia, Latin America and even the Middle East, although no previous study on stock markets in the Pacific region is known. This study therefore contributes to recent literature on technical trading rules by evaluating the performance of technical rules on data obtained from the Australian Stock Exchange – a major stock market in the Pacific region.

The focus of this paper is on two types of simple technical trading rules – moving averages (MA) and trading range breaks (TRB) – which are the types of technical rules typically examined in the literature since Brock, Lakonishok and LeBaron's (1992) study. This selection of technical rules for evaluation is for reasons of comparability – to allow our results to be compared against those obtained in previous research. Broadly speaking, MA rules predict future returns based on the short-run and long-run trends in past prices and emit buy [sell] signals when short-run prices are higher [lower[than the long-run trend. TRB rules, on the other hand, emit buy [sell] signals when the current share price reaches new highs [lows]. As with previous studies, the technical rules are examined both with and without a 1 percent trading band, which is a tool to eliminate whiplash signals.

The empirical analysis is conducted in two stages. The first stage compares returns based on a trading strategy that involves buying and holding the asset following buy signals and selling in favor of the risk-free asset following sell signals against those obtained from the buy-and-hold portfolio equivalent with a series of standard statistical tests. The tests are based on daily stock prices from 1980 through 2002 as well as four non-overlapping sub-samples. Results based on the full sample data show some evidence of predictability, although sub-sample results show technical rules failing to generate abnormal returns from 1991 onwards. As such, our standard test results suggest that informational efficiency in the ASX increased substantially from 1991 onwards.

Nevertheless, we acknowledge that our standard test results, though interesting, do not provide a complete picture on the performance of technical trading rules. Standard statistical tests assume data is normal, independent and identically-distributed (IID-normal), whilst stock returns are known to exhibit non-IID-normal properties such as leptokurtosis, time-varying means and heteroskedasticity. One problem that can arise from this inconsistency is that standard tests show evidence of predictability even when technical rules do not in fact possess predictive ability, simply because of the inability of standard *t*-ratios to address the non-IID-normal properties underlying the empirical data. For the same reason, it is also possible that standard tests find insignificant predictability even when technical trading rules actually possess predictive power. The second stage of analysis is therefore designed to mitigate this problem by using a procedure that employs bootstrap methods to generate empirical distributions under four various models of stock prices – the random walk with drift, AR(1), GARCH(1,1) and EGARCH(1,1) models - to test technical rules. Our results show that, in contrast to existing literature, bootstrap tests reverse standard test outcomes for TRB as well as some MA rules.

The remainder of this paper is structured as follows. Section 2 provides a brief overview of previous research on the application of technical trading rules. Section 3 describes the technical trading rules and data examined in this study. Section 4 presents the results obtained from standard tests, whilst Section 5 provides the results from bootstrap tests. Section 6 concludes and summarizes the findings of this paper.

2.0 Previous Research

Brock, Lakonishok and LeBaron (1992) conducted their study on MA and TRB rules using data from the DJIA over the period 1897 to 1986. The rules were examined using two stages of empirical tests. In the first stage, standard statistical tests were used to evaluate if technical trading rules generate abnormal returns in excess of those obtained from the buy-and-hold equivalent portfolio and their overall results point to technical trading rules having significant predictive power. Their second stage of tests involved the use of bootstrap methods to generate empirical distributions simulated under various models of stock prices, which are then used to test technical rules. Results from their bootstrap tests also show technical rules having significant forecasting power and therefore support their standard test results.

One critique of Brock, Lakonishok and LeBaron's (1992) study, which was raised in the studies by Bessembinder and Chan (1995) and Hudson, Dempsey and Keasey (1996), is the pioneering study's failure to consider transaction costs. Bessembinder and Chan (1995) argue that positive transaction costs apparent in the real world will diminish and can virtually eliminate the abnormal returns from trading. Hence, investors are interested in information on whether the application of technical trading rules can generate abnormal profits after transaction costs rather than whether technical trading rules possess predictive ability. Likewise, Hudson, Dempsey and Keasey (1996) also acknowledge the effects of positive transaction costs on trading profits and argue that profitability testing is relevant for inferences on market efficiency. They refer to Fama (1991), who state that market efficiency is dependent on whether investors are able to exploit the advantages of trading for abnormal profits and not only on whether trading generates abnormal returns prior to the consideration of transaction costs. Hudson, Dempsey and Keasey (1996) therefore argue that where technical rules generate abnormal returns which are then virtually eliminated by high transaction costs, the market is still at least weak form efficient.

Nevertheless, profitability testing is not the only viable method for linking tests of technical trading rules to tests of market efficiency. In Feng and Smith's (1997) study, for example, it was possible to make valid inferences on market efficiency based solely on the evidence obtained from standard statistical tests and bootstrap tests. Their standard test results were similar to those obtained from previous studies and support technical trading rules having significant predictive power. Results from their bootstrap tests did not support standard test results, however, as abnormal returns virtually diminished in tests using empirical distributions simulated under various models of stock prices. In this case, market efficiency is determined because bootstrap test results reverse the standard test outcome of predictability and hence, profitability testing is not necessary.

Another issue surrounding Brock, Lakonishok and LeBaron's (1992) study is the possibility of a data snooping bias in their results. This issue was raised by Sullivan, Timmermann and White (1999), who note that data snooping occurs when research focuses only on the technical rules that perform well historically and the unsuccessful rules are ignored. Over time, the data snooping bias then occurs when the historical record of the small set of successful rules are cited as evidence that technical rules are successful in general. To determine if Brock, Lakonishok and LeBaron's (1992) study is subject to the data snooping bias, Sullivan, Timmermann and White (1999) also examine other types of technical rules including filter, channel break-out and on-balance volume averages rules in addition to the MA and TRB rules examined by Brock, Lakonishok and LeBaron (1992). They found Brock, Lakonishok and LeBaron's (1992) study free from the data snooping bias and that results based on MA and TRB rules for inferences on technical trading rules in general are valid.

3.0 Description of Data and Technical Trading Rules

A. Data

This paper examines daily stock prices from the Australian Stock Exchange (ASX) All Ordinaries index from 1980 January 01 to 2002 December 31. Tests are conducted on the full sample and four non-overlapping sub-samples to verify the stability of results. Each sub-sample is approximately equal in length and represent a different stage of development in the Australian financial economy as set out in Table I.

TABLE I SUB-SAMPLE DATES AND CORRESPONDING EVENTS IN THE AUSTRALIAN FINANCIAL ECONOMY			
SUB-SAMPLE		EVENTS	
I	1980 Jan 01 to 1985 Sep 30	1984	Abolition of fixed scale commission.
			Deregulation of membership into the stock exchange.
II	1985 Oct 01 to 1991 Jun 30	1987	Major stock market downturn in October.
		1990	Failure of several large firms.
III	1991 Jul 01 to 1997 Mar 31	1994	Introduction of the Clearing House Electronic Settlement System (CHESS).
		1995	Implementation of electronic announcement system.
		1996	Full automation of CHESS.
IV	1997 Apr 01 to 2002 Dec 31	1998	Investors gained access to Internet trading via brokers.
		2001	Stamp duty transactions on marketable securities abolished on July 01.
			ASX implemented trading links with North American and Singaporean stock markets.

Therefore, sub-sample I may be summarized as a period of deregulation, sub-sample II a period of economic uncertainty and financial instability and sub-sample III a period of technological advancements in the ASX. Sub-sample IV also contains events that promote technological advancement, whilst also containing events that promote global integration with other stock markets.

B. Technical Trading Rules

This study examines two types of technical rules – moving averages (MA) and trading range breaks (TRB) – both of which emit buy signals to indicate upward price trends and sell signals to indicate downward price trends. MA rules emit buy and sell signals depending on the behavior of a long-run moving average (*LMA*) and a short-run moving average (*SMA*). An MA rule with a short-moving average of 1 trading day and a long-moving average of 50 days is described as an MA (1-50) rule. Two versions of the MA rule are examined. The first version is known as the variable-length moving average (VMA) rule, which detects if prices *are* upward or downward trending and emits buy signals $\{b_t\}$ and sell signals (s_t) as follows:

$$b_t : SMA_t > LMA_t \tag{1}$$

$$s_t : SMA_t < LMA_t$$

This implies that the VMA rule emits either a buy or a sell signal in each trading period and hence, all trading days are classified into either buy or sell days. As such, buy and sell positions are maintained for only one trading day following signal emissions. We examine three VMA rules – the (1-50), (1-150) and (1-200) rules.

The other version of the MA rule examined is the fixed-length moving average (FMA) rule. In this version, buy and sell signals are emitted to detect the *beginning* of upward and downward trends in prices. Buy and sell positions in the stock are then maintained for fixed 10-day holding periods following signal emissions and all other signals emitted within the holding period ignored. We follow Brock, Lakonishok and LeBaron (1992) and examine FMA rules with fixed 10-day holding periods, and hence, buy and sell signals are emitted by the FMA rule as follows:

$$b_t : SMA_t > LMA_t \text{ and } SMA_{t-1} < LMA_{t-1} \text{ and hold for 10 days} \tag{2}$$

$$s_t : SMA_t < LMA_t \text{ and } SMA_{t-1} > LMA_{t-1} \text{ and hold for 10 days}$$

and no signals otherwise. We examine the same three FMA rules – the (1-50), (1-150) and (1-200) rules.

The second type of technical trading rule examined in this study is the trading range break (TRB) rule, which emits buy signals when current prices reach new highs and sell signals when current prices reach new lows. TRB rules are based on the belief that many investors are willing to buy at the maximum price and that such buying pressure creates resistance against a further price rise. However, when the current share price rises above this resistance level, it is an indication that an upward price trend is initiating and a buy signal is then emitted. Similarly, many investors are believed to be willing to sell at the minimum price and such selling pressure then creates support against a further price fall. When the current share price falls below this support level, a sell signal is then emitted to indicate the initiation of a downward price trend. As for the FMA rules, we also examine TRB rules with fixed 10-day holding periods. Therefore, TRB rules emit buy and sell signals as follows:

$$b_t : P_t > \max(P_{t-1},..., P_{t-m}) \text{ and } P_{t-1} < \max(P_{t-1},..., P_{t-m}) \text{ and hold for 10 days} \quad (3)$$

$$s_t : P_t < \min(P_{t-1},..., P_{t-m}) \text{ and } P_{t-1} > \min(P_{t-1},..., P_{t-m}) \text{ and hold for 10 days}$$

where m is the number of previous trading days over which the maximum and minimum prices are determined. We also examine three TRB rules, which are the (1-50), (1-150) and (1-200) rules.

We are also interested in testing the effects of implementing technical trading rules with the 1 percent trading band, which is a tool designed to eliminate false signals. This 1 percent band modifies MA rules by placing a 1 percent band above and below the *LMA* and hence, VMA rules with the 1 percent band emits buy and sell signals as follows:

$$b_t : SMA_t > 1.01LMA_t \tag{4}$$

$$s_t : SMA_t < 0.99LMA_t$$

and no signals when the *SMA* is between 0.99*LMA* and 1.01*LMA*, whilst FMA rules with the 1 percent band emits buy and sell signals according to:

$$b_t : SMA_t > 1.01LMA_t \text{ and } SMA_{t-1} < 1.01LMA_{t-1} \text{ and hold for 10 days} \tag{5}$$

$$s_t : SMA_t < 0.99LMA_t \text{ and } SMA_{t-1} > 0.99LMA_{t-1} \text{ and hold for 10 days}$$

and no signals otherwise. For the case of TRB rules, the 1 percent band is placed above the resistance level and below the support levels such that buy and sell signals are emitted according to:

$$b_t : P_t > 1.01\max(P_{t-1},..., P_{t-m}) \text{ and } P_{t-1} < 1.01\max(P_{t-1},..., P_{t-m}) \text{ and hold for 10 days} \tag{6}$$

$$s_t : P_t < 0.99\min(P_{t-1},..., P_{t-m}) \text{ and } P_{t-1} > 0.99\min(P_{t-1},..., P_{t-m}) \text{ and hold for 10 days}$$

All technical trading rules are examined both with and without the 1 percent band, making a total of 18 rules examined in this paper.

4.0 Empirical Results – Standard Tests

A. Descriptive Statistics

Table II presents descriptive statistics of 1-day and non-overlapping 10-day returns for the full sample and four sub-periods. Statistics for 1-day returns are provided in Panel A and used to compare against trading returns generated by VMA rules, which maintain buy and sell positions in the stock for 1 trading day. Results show a low mean for sub-period II, which is explained by economic uncertainty and financial instability. The mean is however lowest in sub-period IV, a period characterized by stronger global integration. Since sub-period IV also contains the Asian Financial Crisis, which occurred from August 1997, our results support Groenewold's (2003) findings that the Australian share market is more affected by economic events in international economies rather than the domestic economy. Volatility is highest in sub-period II, supporting our explanation that it is a period of financial instability, but decreases in the two most recent sub-periods, which is expected when the measures to enhance market efficiency is implemented. Skewness is negative and highly significant in the full sample, whilst sub-sample results show that this is primarily due to the strong negative Skewness present in sub-periods II and IV. Excess kurtosis is highly significant in the full sample and sub-periods, indicating highly leptokurtic 1-day returns. Serial correlation is highly significant in the full sample, but generally small in sub-samples except for the first and third lags of sub-period I and the first lag of sub-period III.

Descriptive statistics for non-overlapping 10-day returns are provided in Panel B and used to compare against trading returns generated by FMA and TRB rules, which maintain buy and sell positions for fixed 10-day periods. The results for mean and volatility are consistent with the results for 1-day returns. The mean is highest in sub-period III and lowest in sub-periods II and IV, whilst volatility is highest in sub-period II and decreases in the two most recent sub-periods. Skewness is also negative and highly significant, but the sub-sample results in this case only show the presence of significant negative skewness in sub-period II. Excess kurtosis is highly significant in the full sample, but a reduction in kurtosis is observed in the sub-sample results as returns are

TABLE I

SUMMARY STATISTICS FOR DAILY AND NON-OVERLAPPING 10-DAY RETURNS

PANEL A: DAILY RETURNS					
	FULL SAMPLE	SUB SAMPLE I	SUB SAMPLE II	SUB SAMPLE III	SUB SAMPLE IV
N	5701	1200	1200	1201	1201
Mean	0.00026	0.00026	0.00018	0.00030	0.00008
Standard Error	0.00961	0.00855	0.01359	0.00774	0.00825
Skewness	-5.26546**	0.00642	-8.60226**	-0.09283	-0.52304**
Kurtosis	146.25669**	0.76988**	171.55004**	1.03684**	3.64649**
$\rho(1)$	0.113**	0.279**	0.106	0.100**	0.014
$\rho(2)$	-0.049**	-0.043	-0.081	-0.045	-0.039
$\rho(3)$	0.073**	0.078**	0.129	-0.008	0.052
$\rho(4)$	0.048**	0.011	0.120	0.006	0.038
$\rho(5)$	0.034*	0.010	0.077	-0.034	0.009
Bartlett	0.013	0.029	0.029	0.029	0.029
PANEL B: NON-OVERLAPPING 10-DAY RETURNS					
	FULL SAMPLE	SUB SAMPLE I	SUB SAMPLE II	SUB SAMPLE III	SUB SAMPLE IV
N	799	169	169	169	169
Mean	0.00254	0.00245	0.00186	0.00295	0.00080
Standard Error	0.03170	0.03305	0.04816	0.02115	0.02236
Skewness	-3.17879**	-0.03063	-4.25758**	-0.01364	-0.31635
Kurtosis	35.43762**	0.27350	30.81950**	-0.57728	0.75624
$\rho(1)$	0.534**	0.532**	0.603**	0.413**	0.369**
$\rho(2)$	-0.220**	-0.165*	-0.295**	-0.165*	-0.214**
$\rho(3)$	0.049	-0.005	0.129	0.047	0.069
$\rho(4)$	-0.089*	-0.127	-0.086	-0.058	-0.094
$\rho(5)$	-0.010	-0.002	-0.015	0.094	-0.167**
Bartlett	0.035	0.077	0.077	0.077	0.077

Figures marked *(**) are significant at the 5(1) percent level of significance for a two-tailed test.

N is the number of return observations in the sample.

$\rho(i)$ is the autocorrelation at lag *i*.

Bartlett is the Bartlett standard error, $1/\sqrt{N}$, for $\rho(i)$.

only highly leptokurtic in sub-period II. Autocorrelation is significant in the first two lags of the full sample and four sub-periods but generally small in the higher lags.

Descriptive statistics for non-overlapping 10-day returns are provided in Panel B and used to compare against trading returns generated by FMA and TRB rules, which maintain buy and sell positions for fixed 10-day periods. The results for mean and volatility are consistent with the results for 1-day returns. The mean is highest in sub-period III and lowest in sub-periods II and IV, whilst volatility is highest in sub-period II and decreases in the two most recent sub-periods. Skewness is also negative and highly significant, but the sub-sample results in this case only show the presence of significant negative skewness in sub-period II. Excess kurtosis is highly significant in the full sample, but a reduction in kurtosis is observed in the sub-sample results as returns are only highly leptokurtic in sub-period II. Autocorrelation is significant in the first two lags of the full sample and four sub-periods but generally small in the higher lags.

B. Moving Averages

Table III presents the results from testing the application of VMA rules on the ASX All Ordinaries index using standard tests. Full sample results for the individual rules under examination are provided in Panel A and to save space, sub-sample results for rule averages are provided in Panel B.

Columns N_b and N_s report the total number of buy and sell signals respectively. In all cases, N_b exceeds N_s by at least 50 percent. Since VMA rules without the band emits signals in all trading periods, the results suggest that upward price trends are observed 50 percent more frequently than downward price trends. Our results are therefore consistent with an upward trending market over the full sample period.

Figures under column BUY are the differences between the mean buy-period return (M_b) and the mean 1-day return obtained from Table II (*M*), whilst figures under column SELL are the differences between the mean sell-period return (M_s) and *M*. Numbers in parenthesis are the *t*-ratios of testing the differences with a two-tailed test. Where *r* represents either a buy (*b*) or a sell (*s*), the *t*-ratios are computed as[2]:

$$\frac{M_r - M}{\sqrt{\left(s^2 / N_r + s^2 / N \right)}} \tag{7}$$

M_r is either M_b or M_s and N_t is either N_b or N_s. *N* is the number of observations and s^2 is the variance in the 1-day return series obtained from Table II. Since *M* is the normal 1-day mean return, this test essentially examines if the average trading returns in buy periods and in sell periods are significantly different from normal. Technical trading rules are supposed to capture upward price trends in buy periods and downward price trends in sell periods. Hence, we expect M_b to be higher than *M* such that BUY is positive and M_s to be lower than *M* such that SELL is negative. Our results are as expected, although the differences are only significant for the two VMA (1-50) rules and insignificant in the other cases.

Figures under F_b are the fractions of positive buy-period returns and those under F_s are the fractions of negative sell-period returns. We check the usefulness of signals by comparing F_b and F_s. Since prices are expected to rise in buy periods and fall in sell periods, F_b is expected to be higher than F_s where technical rules generate useful signals.

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[2] The variances of returns in buy and in sell periods are assumed to be similar to that of the overall assumption in this paper. It is, however, possible to vary this assumption when conducting two-tailed tests.

Our results show F_b exceeding F_s in all cases, which is consistent with the VMA rules emitting useful signals.

BUY-SELL reports the differences between M_b and M_s and the *t*-ratios of testing the differences with a two-tailed test in parenthesis. The *t*-ratios are computed as[3]:

$$\frac{M_b - M_s}{\sqrt{\left({s^2}/{N_b} + {s^2}/{N_s} \right)}} \tag{8}$$

and hence, this is a test of whether M_b is significantly different from M_s or, in other words, if the BUY-SELL spread is significant. Since technical rules are supposed to generate a higher M_b than M_s where they accurately detect upward and downward price trends, we expect the BUY-SELL spread to be positive. Our findings simply follow from the earlier results for BUY and SELL, and are therefore positive in all cases. As with our earlier results, all BUY-SELL differences are insignificant except for the cases of the two VMA (1-50) rules.

Sub-sample results for rule-averages in Panel B show the average Buy difference decreasing and the average Sell difference increasing as sub-periods are more recent. These results lead to a decreasing average Buy-Sell spread over time, which is consistent with VMA rules losing predictive ability as sub-periods are more recent.

[3] As per footnote 1.

TABLE III

STANDARD TEST RESULTS FOR THE VARIABLE MOVING AVERAGES (VMA)

PANEL A: FULL SAMPLE

SAMPLE	VMA RULES	N_b	N_s	BUY	SELL	F_B	F_S	BUY-SELL
FULL	(1,50,0)	3385	2316	0.00042*	-0.00062**	0.52142	0.48359	0.00104**
				(2.02404)	(-2.60502)			(4.00901)
	(1,50,0.01)	2806	1828	0.00048*	-0.00079**	0.52388	0.47921	0.00128**
				(2.18244)	(-3.06967)			(4.41947)
	(1,150,0)	3759	1942	0.00012	-0.00023	0.51689	0.48507	0.00034
				(0.57760)	(-0.89403)			(1.27481)
	(1,150,0.01)	3380	1696	0.00011	-0.00037	0.51598	0.47642	0.00048
				(0.52716)	(-1.41049)			(1.69563)
	(1,200,0)	3840	1861	0.00008	-0.00016	0.51823	0.48092	0.00023
				(0.38087)	(-0.61453)			(0.86238)
	(1,200,0.01)	3584	1610	0.00008	-0.00020	0.51814	0.47950	0.00029
				(0.41213)	(-0.74898)			(0.99738)
	AVERAGE			0.00022	-0.00040			0.00061

PANEL B: SUB SAMPLES

SAMPLE	VMA RULES	BUY	SELL	BUY-SELL
SUB I	AVERAGE	0.00059	-0.00082	0.00141
SUB II	AVERAGE	0.00052	-0.00080	0.00132
SUB III	AVERAGE	0.00013	-0.00021	0.00034
SUB IIV	AVERAGE	-0.00013	0.00022	-0.00034

N_b and N_s are the number of BUY and SELL signals respectively.

BUY(SELL) is the difference between the mean return in BUY(SELL) periods and the unconditional mean.

F_b (F_s) is the fraction of BUY(SELL) returns greater than 0.

BUY-SELL is the difference between the mean BUY period return and mean SELL period return.

Numbers in parentheses are test statistics for a two-tailed test.

Figures marked *(**) are significant at the 5(1) percent level of significance.

Table IV provides the results of applying FMA rules to the ASX All Ordinaries index. As with Table III, we present full sample results for individual rules in Panel A and sub-sample results for rule averages in Panel B. We begin this discussion by describing the results in Panel A. N_b and N_s have much smaller values compared to those for VMA rules. This is expected since FMA rules only emit signals on certain trading days and maintain positions for fixed 10-day periods. We find N_b and N_s approximately equal for FMA rules without the band whilst FMA rules with the band tend to have higher values for N_b and lower values for N_s. Since FMA rules do not emit signals in all trading periods, our results have no direct implications on whether the market is upward or downward trending over the same period and hence, plausible.

BUY is positive for five of the six FMA rules, of which three are significant. Only the FMA (1-200-0.01) rule has a negative BUY difference, although only at an insignificant level. SELL is negative for all FMA rules and significant for three cases. These translate into positive Buy-Sell differences for all six FMA rules, with all except the FMA (1-200-0.01) rule being significant at the 1 percent level. We find that all FMA rules generate useful signals as F_b exceeds F_s in all cases. Our results are therefore consistent with FMA rules having significant predictive power. The effects of introducing the 1 percent trading band to FMA rules are also different from those observed for VMA rules. In this case, the 1 percent band increases the profitability for only the FMA (1-50) rules, but leads to smaller BUY-SELL spreads for the remaining FMA rules.

TABLE IV

STANDARD TEST RESULTS FOR THE FIXED-LENGTH MOVING AVERAGES (FMA)

PANEL A: FULL SAMPLE

SAMPLE	FMA RULES	N_b	N_s	BUY	SELL	F_B	F_S	BUY-SELL
FULL	(1,50,0)	1490	1490	0.00355*	-0.00768**	0.05772	0.04765	0.01124**
				(2.55610)	(-5.52765)			(9.67492)
	(1,50,0.01)	1680	1330	0.00881**	-0.01088**	0.06607	0.04436	0.01969**
				(6.46976)	(-7.66807)			(16.92652)
	(1,150,0)	890	900	0.00539**	-0.00094	0.06854	0.05778	0.00633**
				(3.488819)	(-0.60755)			(4.22149)
	(1,150,0.01)	1120	700	0.00128	-0.00388*	0.05357	0.04571	0.00516**
				(0.38412)	(-2.36245)			(3.37511)
	(1,200,0)	720	730	0.00251	-0.00253	0.05972	0.05068	0.00504**
				(1.54104)	(0.11997)			(3.02418)
	(1,200,0.01)	870	730	-0.00027	-0.00216	0.05287	0.05342	0.00189
				(-1.32941)	(-1.32941)			(1.18482)
	AVERAGE			0.00355	-0.00468			0.00823

PANEL B: SUB SAMPLES

SAMPLE	FMA RULES	BUY	SELL	BUY-SELL
SUB I	AVERAGE	0.01723	-0.00668	0.02391
SUB II	AVERAGE	0.00354	-0.02278	0.02633
SUB III	AVERAGE	-0.00241	-0.00039	-0.00186
SUB IIV	AVERAGE	-0.00012	-0.00130	0.00119

N_b and N_s are the number of BUY and SELL signals respectively.

BUY(SELL) is the difference between the mean return in BUY(SELL) periods and the unconditional mean.

F_b (F_s) is the fraction of BUY(SELL) returns greater than 0.

BUY-SELL is the difference between the mean BUY period return and mean SELL period return.

Numbers in parentheses are test statistics for a two-tailed test.

Figures marked *(**) are significant at the 5(1) percent level of significance.

Sub-sample results for rule averages in Panel B show large and positive Buy-Sell spreads in the first two sub-periods, but which decrease in the two most recent sub-periods. Our sub-sample results for FMA rules are therefore similar to those for VMA rules and indicate a loss of predictive power over time.

C. Trading Range Breaks

Table V presents the standard test results for TRB rules, which is divided into full sample results for individual rules in Panel A and sub-sample results for rule averages in Panel B. We begin by describing Panel A's results, which also show smaller values for N_b and N_s compared to those generated by VMA rules. Again, these results are expected since TRB rules only emit signals on certain trading days and also maintain buy and sell positions for fixed 10-day periods. N_b exceeds N_s in all cases, although like the results for FMA rules, these findings have no direct implications on whether the market is upward or downward trending since signals are not emitted in all trading days.

BUY is positive and significant in all cases, indicating that TRB rules are successful at predicting upward price trends. SELL, on the other hand, is dependent on whether the 1 percent band is introduced. TRB rules without the 1 percent band generate negative SELL differences and two of which are significant at the 1 percent level. On the other hand, TRB rules with the 1 percent band generate positive SELL differences, which are generally insignificant except for the TRB (1-200-0.01) rule. Nonetheless, Buy-Sell is still positive and significant for five of the six cases and insignificantly negative only in the case of the TRB (1-200-0.01) rule. Our results also show F_b exceeding F_s for all

TABLE V

STANDARD TEST RESULTS FOR THE TRADING RANGE BREAKS (TRB)

PANEL A: FULL SAMPLE

SAMPLE	TRB RULES	N_b	N_s	BUY	SELL	F_B	F_S	BUY-SELL
FULL	(1,50,0)	2970	1520	0.00379**	-0.00432**	0.06162	0.05066	0.00811**
				(2.99930)	(-3.11856)			(8.11119)
	(1,50,0.01)	990	830	0.00424**	0.00074	0.06162	0.05904	0.00350*
				(2.81281)	(0.46962)			(2.34778)
	(1,150,0)	2150	750	0.00323*	-0.00534**	0.06093	0.04667	0.00856**
				(2.45656)	(-3.31199)			(6.37072)
	(1,150,0.01)	640	480	0.00701**	0.00294	0.06406	0.06458	0.00407*
				(4.16942)	(1.60783)			(2.12532)
	(1,200,0)	1920	650	0.00400**	-0.00241	0.06198	0.04769	0.00641**
				(2.99487)	(-1.43989)			(4.45443)
	(1,200,0.01)	580	370	0.00706**	0.00921**	0.06379	0.06757	-0.00215
				(4.08084)	(4.62017)			(-1.02083)
	AVERAGE			0.00489	0.00014			0.00475

PANEL B: SUB SAMPLES

SAMPLE	TRB RULES	BUY	SELL	BUY-SELL
SUB I	AVERAGE	0.00941	-0.00619	0.01560
SUB II	AVERAGE	0.01919	-0.00948	0.02868
SUB III	AVERAGE	-0.0559	0.00472	-0.01032
SUB IV	AVERAGE	-0.00993	0.00987	-0.01979

N_b and N_s are the number of BUY and SELL signals respectively.

BUY(SELL) is the difference between the mean return in BUY(SELL) periods and the unconditional mean.

F_b (F_s) is the fraction of BUY(SELL) returns greater than 0.

BUY-SELL is the difference between the mean BUY period return and mean SELL period return.

Numbers in parentheses are test statistics for a two-tailed test.

Figures marked *(**) are significant at the 5(1) percent level of significance.

TRB rules except the (1-200-0.01) rule, which is consistent with all but one of the TRB rules generating useful signals. Due to the effects of the 1 percent band on SELL differences, we find that the band tends to decrease the BUY-SELL spread for TRB rules.

Sub-sample results in Panel B show positive average BUY-SELL spreads in the first two sub-samples, but which turn negative in the two most recent sub-periods. Our sub-sample results for TRB rules are therefore consistent with earlier findings for VMA and FMA rules that there is a loss of predictive power over time.

D. Discussion and Comparison with Previous Research

Based on our full sample results, we find that FMA and TRB rules possess significant predictive power whilst VMA rules are generally weak when applied to the ASX. This is in contrast to the results obtained by Brock, Lakonishok and LeBaron (1992) and Hudson, Dempsey and Keasey (1996), who find VMA rules more significant than either the FMA or TRB rules. One explanation offered by Hudson, Dempsey and Keasey (1996) is that VMA rules perform better when applied to longer data samples. Brock, Lakonishok and Lebaron (1992) employ 90 years of daily data whilst Hudson, Dempsey and Keasey (1996) use 60 years of data. Our data sample spans only 23 years and is much smaller than the sample lengths used in both studies. Hence, our results support the notion that the performance of VMA rules is sensitive to the sample length employed.

We also find the effects of introducing the 1 percent band dependent on which type of technical rule is implemented. When introduced to VMA rules, the 1 percent band always increases the BUY-SELL spread whilst with FMA rules, the effects on profitability are ambiguous. Introducing the 1 percent band to TRB rules, on the other hand, always leads to smaller BUY-SELL spreads and a decrease in profitability. Since the loss of profits is only limited to technical rules with fixed holding periods, one possible explanation for the different effects on profitability is that the band leads to later detection of upward and downward price trends and hence, the loss of potential profits that could be obtained with early signals.

It is also interesting to note that our sub-sample results for the different types of technical rules generally exhibit the same trend over time – the average Buy-Sell spreads of VMA, FMA and TRB rules are large and positive in the first two sub-periods but then turn negative in the two most recent sub-periods. Our results are therefore in contrast to the results obtained by Brock, Lakonishok and LeBaron (1992) and Hudson, Dempsey and Keasey (1996), who find the significance of technical rules similar across different sub-periods. Instead, our results are similar to Mills' (1997), who also finds VMA, FMA and TRB rules losing predictive power over time when applied to UK stock prices and who attribute the phenomenon to a rise of informational efficiency over time. When we look at the events that occurred in the sub-samples, we find that the ASX implemented measures to promote technological advancement in sub-period III and global integration in sub-period IV. Since technological advancement is known to promote informational efficiency, our results support Mills' (1997) explanation.

5.0 Empirical Results – Bootstrap Tests

We acknowledge that our standard test results, although interesting, do not provide a complete picture on the performance of technical trading rules. Standard tests assume data is normal, independent and identically distributed (IID-normal), whilst stock returns are known to exhibit non-IID-normal properties such as non-normality, autocorrelation, leptokurtosis and conditional heteroskedasticity. One problem that can arise from this inconsistency is that the standard tests show significant predictability when technical rules do not in fact possess forecasting power, simply because of the inability of *t*-ratios to address the non-IID-normal characteristics underlying empirical data. Similarly, standard tests may also find insignificant predictability when technical rules actually possess forecast power. A second procedure that bootstraps the tests to capture the characteristics of the data is used to mitigate this problem. Broadly speaking, this procedure involves generating empirical distributions simulated under various models of stock prices with bootstrap methods, which are used to re-examine technical trading rules to determine if addressing the specific non-IID-normal properties represented by the model under simulation affects the standard test outcome of predictability.

The following describes the bootstrap procedure in greater detail[4]. To estimate the expected trading returns conditional on buy and sell signals, the series of *h*-day returns is first constructed by setting:

$$R_t^h = \log(P_{t+h}) - \log(P_t) \tag{9}$$

where R_t^h is the *h*-day return of holding the stock from day *t* to *t*+*h* and *P* is stock prices. Let m_b denote the expected return conditional on a buy signal such that:

$$m_b = E(R_t^h \mid b_t) \tag{10}$$

and m_s denotes the expected return conditional on a sell signal such that:

[4] Refer to Brock, Lakonishok and LeBaron (1992) for a full description of the bootstrap procedure.

$$m_s = E\left(R_t^h \mid s_t\right) \tag{11}$$

The procedure estimates m_b and m_s from the original ASX data, which are then compared against their empirical distributions simulated under various models of stock prices.

Empirical distributions simulated under each model of stock prices consists of 500 replications of m_b and m_s. In this paper, we simulate empirical distributions under four models of stock prices – the (i) random walk with drift model, (ii) autoregressive of order one, or AR(1), (iii) generalized autoregressive heteroskedasticity (1,1), or GARCH(1,1) model and the (iv) exponential GARCH(1,1) or EGARCH(1,1) model. According to the random walk with drift model, stock prices follow a random walk with drift:

$$\log(P_t) = c + \log(P_{t-1}) + \varepsilon_t \tag{12}$$

where *c* is the constant parameter representing the drift and ε_t is the random error term with an expected mean of 0. This implies that expected stock returns (X_t) are equal to *c*:

$$E(X_t) = c \tag{13}$$

In other words, the random walk with drift model states that stock prices are independent and identically distribution (IID), but non-normal. This is also an implication of the EMH and hence, tests based on the random walk with drift simulations also examine if stock returns behave as implied by the EMH.

The second model for simulation is the AR(1) model, which states:

$$X_t = a + bX_{t-1} + \varepsilon_t, \quad |b| < 1 \tag{14}$$

where *a* and *b* are parameters. The AR(1) model assumes that X_t is dependent on X_{t-1} or, in other words, that stock returns are time-dependent and serially correlated. Tests based on the AR(1) simulations therefore evaluate if addressing time-dependent means in the data affects the standard test outcome.

The third model for simulation is the GARCH(1,1) model, which states:

$$X_t = a - b\varepsilon_{t-1} + \varepsilon_t \tag{15}$$

$$H_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta H_{t-1}$$

$$\varepsilon_t = \sqrt{H_t}Z_t \qquad Z_t \sim N(0,1)$$

where ε_t is the conditionally normally distributed and serially uncorrelated error term and Z_t is standardized estimated residuals. H_t is the conditional variance, which is defined as a linear function of the previous period's conditional variance (H_{t-1}) and squared error term (ε_{t-1}^2). Hence, the model assumes that periods of high volatility will be followed by periods of higher volatility and periods of low volatility followed by periods of lower volatility. An MA(1) component (ε_{t-1}) is also included in the conditional mean to account for short-run autocorrelations and time-varying conditional means in the data and hence, empirical distributions under the GARCH(1,1) model are used to evaluate if time-varying conditional means and variances in the data affects the standard test outcome.

The last model for simulation is the EGARCH(1,1) model, which states:

$$X_t = a - b\varepsilon_{t-1} + \varepsilon_t \tag{16}$$

$$H_t = e^{\alpha_0 + \omega G(Z_{t-1}) + \beta H_{t-1}}$$

$$G(Z_t) = |Z_t| - (2/\pi)^{1/2} - \theta Z_t$$

$$\varepsilon_t = \sqrt{H_t} Z_t \qquad Z_t \sim N(0,1)$$

The EGARCH(1,1) model also captures time-varying conditional volatilities, but differs from the GARCH(1,1) model in two respects. First, the log of the conditional variance now follows an autoregressive process and second, previous returns are allowed to affect future volatility differently depending on whether they are positive or negative due to the *G* function. The EGARCH(1,1) model also includes an MA(1) component to account for short-run autocorrelations in the data and hence, empirical distributions simulated under the EGARCH(1,1) model are used to evaluate if time-varying conditional means and volatilities with asymmetric responses in the conditional variance to positive and negative past returns affects the standard test outcome.

A. Parameter Estimates

Table VI contains parameter estimates for the AR(1), GARCH(1,1) and EGARCH(1,1) models for the full sample and four sub-periods. Panel A provides parameter estimates for the AR(1) model, which are obtained using OLS regressions. The full sample results indicate that X_{t-1} is highly significant in explaining X_t, implying that returns are strongly serially correlated over the full sample period. However, sub-sample results show X_{t-1} losing significance as the sub-periods are more recent and that in sub-period IV, X_{t-1} is insignificant. Our results show that current returns are less dependent on past returns as sub-periods are more recent, which support earlier findings that informational efficiency in the ASX increased over time.

TABLE VI

PARAMETER ESTIMATES FOR THE AR(1), GARCH(1,1) AND EGARCH(1,1) MODELS

PANEL A – AR(1) PARAMETER ESTIMATES

$$X_t = a + bX_{t-1} + \varepsilon_t$$

SAMPLE	a	b
FULL	0.00026 (2.07751)	0.11515 (8.98486)
SUB I	0.00032 (1.42410)	0.24710 (9.90564)
SUB II	0.00024 (0.73014)	0.10965 (4.26717)
SUB III	0.00027 (1.36632)	0.08036 (3.12246)
SUB IV	0.00016 (0.73010)	0.00682 (0.26394)

PANEL B – GARCH(1,1) PARAMETER ESTIMATES

$$X_t = a - b\varepsilon_{t-1} + \varepsilon_t \qquad \varepsilon_t = H_t^{1/2} Z_t$$

$$H_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta H_{t-1}$$

$$Z_t \sim N(0,1)$$

SAMPLE	a	b	α_0	α_1	β
FULL	0.00049 (3.98761)	-0.19110 (-12.50027)	1.34e-05 (13.67740)	0.24090 (51.58676)	0.60770 (37.19803)
SUB I	0.00058 (2.08087)	-0.30840 (-10.99638)	6.66e-06 (4.63412)	0.14980 (6.74847)	0.76420 (21.33722)
SUB II	0.00052 (2.16951)	-0.27760 (-8.97145)	1.99e-05 (7.92823)	0.50550 (24.52988)	0.40710 (11.72125)
SUB III	0.00033 (1.48641)	-0.10900 (-3.87335)	1.04e-05 (2.68067)	0.06340 (3.05808)	0.75760 (9.22446)
SUB IV	0.00041 (1.93003)	-0.02560 (-0.93760)	4.96e-06 (4.13829)	0.121946 (9.02324)	0.81010 (29.40988)

PANEL C – EGARCH(1,1) PARAMETER ESTIMATES						
	$X_t = a - b\varepsilon_{t-1} + \varepsilon_t \qquad \varepsilon_t = H_t^{1/2} Z_t$ $H_t = e^{\alpha_0 + \omega G(Z_{t-1}) + \beta H_{t-1}}$ $G(Z_t) = \lvert Z_t \rvert - (2/\pi)^{1/2} - \theta Z_t$ $Z_t \sim N(0,1)$					
SAMPLE	a	b	α_0	β	θ	ω
FULL	0.00032 (2.69305)	-0.18444 (-13.38718)	-1.42719 (-15.58012)	0.84910 (89.07783)	0.29316 (10.09493)	0.35888 (34.96194)
SUB I	0.00063 (2.25113)	-0.31065 (-11.51476)	-0.88123 (-4.73700)	0.90747 (46.66621)	0.04676 (0.75979)	0.26729 (7.86975)
SUB II	0.00012 (0.45132)	-0.25386 (-8.11586)	-2.47263 (-11.67963)	0.73216 (32.51491)	0.20604 (4.36880)	0.68696 (23.85791)
SUB III	0.00022 (1.00098)	-0.10273 (-3.69156)	-0.96315 (-3.28370)	0.90111 (30.08788)	0.76130 (2.81862)	0.09852 (3.47002)
SUB IV	0.00012 (0.60304)	-0.02827 (-1.15357)	-0.47150 (-5.04071)	0.95088 (98.52180)	0.87157 (5.79972)	0.14127 (7.35082)

OLS is used to estimate the AR(1) and maximum likelihood is used to estimate the GARCH(1,1) and EGARCH(1,1).

X_t is the continuously compounded return on day *t* and H_t is the conditional variance on day *t*.

Numbers in parenthesis are *t*-ratios.

Panel B provides parameter estimates for the GARCH(1,1) model, which are estimated using maximum likelihood. Full sample results show that ε_{t-1}^2 and H_{t-1} are highly significant in estimating H_t, implying that the variance of ASX returns is conditional and time-varying. Sub-sample results are similar and show no signs that the significance of ε_{t-1}^2 and H_{t-1} are decreasing over time. The MA(1) component, ε_{t-1}, is highly significant in the full sample but sub-sample results show ε_{t-1} losing significance over time and that ε_{t-1} is insignificant in sub-period IV. Results for ε_{t-1} are therefore consistent with the AR(1) estimates.

Panel C provides parameter estimates for the EGARCH(1,1) model, which is also obtained using maximum likelihood. Overall results are similar to those obtained for the GARCH(1,1) model, with the exception that θ is also highly significant in the full sample and in sub-periods II, III and IV. The results therefore implies that in the full sample and sub-periods II, III and IV, past returns and future volatility are inversely related.

B. Random Walk with Drift Process

Table VII provides the results of testing technical trading rules using random walk with drift simulations for the full sample. The test is designed to evaluate if addressing non-normality in the data affects the standard test outcome of predictability which, at the same time, also examines if technical trading returns conform to implications of the EMH.

BUY reports the fractions of simulated expected means conditional on buy signals greater than the ASX estimate. Where expectations from simulations are differentiated by an asterisk (*), BUY reports the fractions of m_b^* greater than m_b. Since technical rules are supposed to generate positive returns in buy periods, the simulations are expected to replicate values of m_b^* at least as large as m_b and therefore, BUY should be equal or greater than 0.05 is technical rules are significant after accounting for non-normality in the data or smaller than 0.05 if technical rules are insignificant after the random walk simulations are used. SELL reports the fractions of m_s^* greater than m_s. Because technical rules are supposed to generate negative returns in sell periods, the simulations are expected to replicate values of m_s^* at least as small as m_s and hence, SELL is expected to be 0.95 or larger where technical rules are significant after addressing for non-normality. The interpretation of BUY-SELL, which reports the fractions of (m_b^* - m_s^*) greater than (m_b - m_s) is similar to that for BUY, since the expected BUY-SELL spread is significant if technical rules are significant.

We now proceed to describe the results for VMA rules presented in Table VII. A simulated BUY *p*-value of 0.006 for the VMA (1-50-0) rule implies that only 3 of the 500 simulations replicate a value for m_b^* greater than m_b and that Buy is still significant after accounting for non-normality in the data. The VMA (1-50-0) rule has a simulated SELL *p*-value of 1.00, which implies that all simulations generate a value for m_s^* greater than m_s. Therefore, SELL is still significant after non-normality in the data is addressed. Our results therefore indicate that non-normality in the data does not affect the standard test outcome of predictability in buy and in sell periods for the VMA (1-50-0) rule. The VMA (1-50-0) rule has a BUY-SELL *p*-value of 0.00, which implies that none of the simulations generate a value for (m_b^* - m_s^*) greater than (m_b - m_s). Therefore, non-normality does not affect the standard test outcome of significance for the VMA (1-50-0) rule. Results for the VMA (1-50-0.01) rule are also similar and support standard test results. In all the other cases, BUY, SELL and BUY-SELL are insignificant, as consistent with the standard test results. Overall, these results imply that non-normality in the data does not affect the standard test results for VMA rules.

TABLE VII

TEST RESULTS FROM RANDOM WALK WITH DRIFT SIMULATIONS

FULL SAMPLE: 1980:01:01 – 2002:12:31			
RULES	BUY	SELL	BUY-SELL
VMA (1, 50, 0)	0.00600	1.00000	0.00000
VMA (1, 50, 0.01)	0.01400	1.00000	0.00000
VMA (1, 150, 0)	0.31600	0.91000	0.14000
VMA (1, 150, 0.01)	0.32000	0.95800	0.08200
VMA (1, 200, 0)	0.40800	0.82600	0.26200
VMA (1, 200, 0.01)	0.39000	0.86400	0.23800
FMA (1, 50, 0)	0.27600	0.99600	0.00000
FMA (1, 50, 0.01)	0.00200	1.00000	0.00000
FMA (1, 150, 0)	0.12200	0.68200	0.02000
FMA (1, 150, 0.01)	0.41400	0.85800	0.15800
FMA (1, 200, 0)	0.44200	0.79800	0.05800
FMA (1, 200, 0.01)	0.58200	0.77000	0.36200
TRB (1, 50, 0)	0.10200	0.94000	0.02400
TRB (1, 50, 0.01)	0.17600	0.37000	0.29200
TRB (1, 150, 0)	0.15200	0.89000	0.07400
TRB (1, 150, 0.01)	0.13600	0.11200	0.28400
TRB (1, 200, 0)	0.14000	0.77400	0.11800
TRB (1, 200, 0.01)	0.13200	0.00400	0.51800

Numerical values are the fractions of simulations generating a mean larger than that from the ASX data.

The results for FMA rules are quite different. BUY and SELL are significant for the FMA (1-50-0.01) rule, but insignificant in all the other cases. In contrast, standard test results show a total of 3 significant results for each BUY and SELL. Therefore, we find that non-normality affects the standard test results for BUY and SELL in some cases. We also find BUY-SELL significant in only 3 cases, whereas standard tests show 5 significant BUY-

SELL spreads. Overall, the results for FMA rules imply that non-normality in the data affects the standard test outcome of predictability in some cases.

The results for TRB rules show insignificant BUY and SELL *p*-values for all six TRB rules. In contrast, standard tests find Buy significantly positive in 3 cases and Sell significantly negative in also 3 cases. Similarly, the results for BUY-SELL do not support standard test results as the simulations only generate one significant BUY-SELL *p*-value compared with four significant BUY-SELL spreads indicated by standard tests. Overall, our results suggest that non-normality in the data affects the standard test outcome of predictability for most TRB rules. It is also interesting to note that the SELL *p*-value for the (1-200-0.01) is significantly positive at the value of 0.005. Standard tests, on the other hand, find that the TRB (1-200-0.01) rule only generates an insignificantly positive Sell difference, which implies that in this case, non-normality affects the standard test outcome of *insignificance*.

Sub-sample results are similar and therefore not presented to avoid repetition. To summarize our findings from tests based on random walk simulations, we find that non-normality affects the standard test outcome of technical rules differently depending on which type of technical rule is under investigation.

C. AR(1) Process

Table VII presents the results of tests with the AR(1) simulations. This test is designed to determine if time-dependent means in the data affects standard test results.

TABLE VIII

TEST RESULTS FROM AR(1) SIMULATIONS

FULL SAMPLE: 1980:01:01 – 2002:12:31			
RULES	BUY	SELL	BUY-SELL
VMA (1, 50, 0)	0.00800	1.00000	0.00000
VMA (1, 50, 0.01)	0.01400	0.99800	0.00000
VMA (1, 150, 0)	0.27800	0.90000	0.14000
VMA (1, 150, 0.01)	0.32200	0.95800	0.10000
VMA (1, 200, 0)	0.37200	0.84800	0.23600
VMA (1, 200, 0.01)	0.34800	0.85200	0.22800
FMA (1, 50, 0)	0.25600	0.99200	0.00000
FMA (1, 50, 0.01)	0.00200	0.99800	0.00000
FMA (1, 150, 0)	0.13800	0.68600	0.02200
FMA (1, 150, 0.01)	0.41800	0.84200	0.18400
FMA (1, 200, 0)	0.40200	0.77800	0.07000
FMA (1, 200, 0.01)	0.60800	0.75200	0.38600
TRB (1, 50, 0)	0.13800	0.92800	0.03600
TRB (1, 50, 0.01)	0.18400	0.31600	0.29000
TRB (1, 150, 0)	0.13800	0.91400	0.06800
TRB (1, 150, 0.01)	0.10200	0.10800	0.27800
TRB (1, 200, 0)	0.11000	0.73600	0.11200
TRB (1, 200, 0.01)	0.17600	0.00200	0.55800

Numerical values are the fractions of simulations generating a mean larger than that from the ASX data.

We begin by discussing the results for VMA rules, which show significant *p*-values for BUY, SELL and BUY-SELL for the two VMA (1-50) rules and insignificant BUY, SELL and BUY-SELL *p*-values in the other cases. Again, the simulation results are consistent with standard tests and imply that time-dependent means do not affect the standard test results for VMA rules. Our results for FMA rules are also ambiguous. The simulated *p*-values for BUY and SELL are all insignificant except in the case of the FMA (1-50-0.01) rule, whilst the simulated *p*-values for BUY-SELL are only significant in 3 cases. Meanwhile, our results for TRB rules similarly show insignificant *p*-values for Buy and Sell in all cases. The results translate into insignificant Buy-Sell *p*-values for all TRB rules, except the (1-50-0) rule. Therefore, our results indicate that time-dependent means in the data affects the standard test outcome of predictability for most TRB rules. We also find the AR(1) simulated Sell *p*-value for the TRB(1-200-0.01) rule smaller than 0.05, implying that Sell is positive and significant after addressing for time-dependent means.

Sub-sample results are similar and not presented to save space. Overall, we find the results of tests based on the AR(1) simulations very similar to those based on the random walk simulations and that time-dependent means affects the standard test outcome of predictability differently depending on which type of technical rules is under examination.

D. GARCH(1,1) Process

Table IX presents the results of testing technical rules with GARCH(1,1) simulations. With this test, we examine if time-dependent conditional means and variances in the data affects standard test results.

We begin by looking at the results for VMA rules. Buy is greater than 0.05 in all cases, whilst Sell is smaller than 0.95 for all but the VMA (1-50-0.01) rule. This implies that the significant results obtained earlier, but which are now insignificant, are due to the ignored presence of time-varying conditional variances in the data. Nevertheless, both VMA (1-50) rules still have Buy-Sell *p*-values smaller than 0.05, implying that time-

TABLE IX

TEST RESULTS FROM GARCH(1,1) SIMULATIONS

FULL SAMPLE: 1980:01:01 – 2002:12:31			
RULES	BUY	SELL	BUY-SELL
VMA (1, 50, 0)	0.18800	0.94200	0.04000
VMA (1, 50, 0.01)	0.22600	0.95400	0.02000
VMA (1, 150, 0)	0.53800	0.63600	0.50200
VMA (1, 150, 0.01)	0.62400	0.76200	0.46200
VMA (1, 200, 0)	0.60000	0.54400	0.56000
VMA (1, 200, 0.01)	0.58600	0.64800	0.53200
FMA (1, 50, 0)	0.47800	0.92200	0.01800
FMA (1, 50, 0.01)	0.03600	0.98600	0.00000
FMA (1, 150, 0)	0.24600	0.35800	0.36800
FMA (1, 150, 0.01)	0.58000	0.57200	0.53000
FMA (1, 200, 0)	0.55200	0.53400	0.54800
FMA (1, 200, 0.01)	0.76200	0.47000	0.75200
TRB (1, 50, 0)	0.22600	0.74400	0.17600
TRB (1, 50, 0.01)	0.49200	0.11400	0.74200
TRB (1, 150, 0)	0.29000	0.69600	0.24400
TRB (1, 150, 0.01)	0.33400	0.05000	0.62800
TRB (1, 200, 0)	0.24600	0.52000	0.26800
TRB (1, 200, 0.01)	0.36200	0.00000	0.81600
Numerical values are the fractions of simulations generating a mean larger than that from the ASX data.			

dependent conditional means and variances in the data do not affect the standard test outcome of predictability.

As with our earlier findings, the results for FMA rules show Buy *p*-values greater than 0.05 in all cases and Sell *p*-values smaller than 0.95 for all but the FMA (1-50-0.01) rule. However, the Buy-Sell *p*-values in this case are all insignificant except for the two FMA

(1-50) rules. This implies that the significant Buy-Sell *p*-value for the FMA (1-150-0) rule obtained earlier, but which is now insignificant, is due to the ignored presence of time-varying conditional variances in the data. Nevertheless, we still find the results for FMA rules ambiguous and that time-varying conditional means and variances in the data affects the standard test outcome of predictability for some FMA rules.

Also similar with earlier findings, the results for TRB rules show Buy greater than 0.05 and Sell smaller than 0.95 in all cases. However, all the Buy-Sell *p*-values are now greater than 0.05, which implies that time-varying conditional means and variances reverses the standard test outcome of predictability for all significant TRB rules. Again, we find that the earlier significant Buy-Sell *p*-value for the TRB(1-50-0) rule is explained by the ignored presence of time-varying conditional variances in the data.

Sub-sample results are consistent and therefore not presented to avoid repetition. Overall, we find that time-dependent conditional means and variances in the data affects a higher number of technical rules compared to time-dependent means or non-normality alone, although Buy-Sell spreads are still significant in some cases.

E. EGARCH(1,1) Process

Table X provides the results of testing technical trading rules with EGARCH(1,1) simulations. With this test, we also examine if time-varying conditional means and variances affects standard test results except that now, positive and negative past returns are allowed to affect future volatility differently.

TABLE X

TEST RESULTS FROM EGARCH(1,1) SIMULATIONS

FULL SAMPLE: 1980:01:01 – 2002:12:31			
PANEL A – INDIVIDUAL RULES			
RULES	BUY	SELL	BUY-SELL
VMA (1, 50, 0)	0.19400	0.92600	0.04400
VMA (1, 50, 0.01)	0.24200	0.96200	0.03600
VMA (1, 150, 0)	0.52200	0.61600	0.49400
VMA (1, 150, 0.01)	0.59000	0.78800	0.42400
VMA (1, 200, 0)	0.58400	0.54200	0.57200
VMA (1, 200, 0.01)	0.55600	0.58800	0.51400
FMA (1, 50, 0)	0.48400	0.93600	0.01600
FMA (1, 50, 0.01)	0.02400	0.98400	0.00000
FMA (1, 150, 0)	0.25400	0.35000	0.34200
FMA (1, 150, 0.01)	0.58000	0.55400	0.49000
FMA (1, 200, 0)	0.59000	0.52200	0.56400
FMA (1, 200, 0.01)	0.75400	0.51600	0.65600
TRB (1, 50, 0)	0.22400	0.73800	0.17600
TRB (1, 50, 0.01)	0.51200	0.11000	0.76400
TRB (1, 150, 0)	0.30200	0.71000	0.24800
TRB (1, 150, 0.01)	0.35800	0.05000	0.65200
TRB (1, 200, 0)	0.24000	0.53400	0.27600
TRB (1, 200, 0.01)	0.38800	0.00000	0.83000
Numerical values are the fractions of simulations generating a mean larger than that from the ASX data.			

Our results are very similar to those obtained using GARCH(1,1) simulations. Buy-Sell is smaller than 0.05 for both VMA (1-50) rules but insignificant in the other four cases. Results for FMA rules show significant Buy-Sell *p*-values for both FMA (1-50) rules and insignificant *p*-values in the other cases. TRB rules generate insignificant Buy-Sell *p*-values in all cases. Sub-sample results are also very similar and hence, we find that additionally allowing for asymmetric responses in future volatility to positive and negative past returns does not affect the results that can be obtained by addressing time-varying conditional means and variances alone.

F. Discussion and Comparison with Previous Research

We find that our bootstrap results are different depending on which type of technical rule is under investigation. Simulation test results for VMA rules are generally consistent with standard test results. Results for FMA rules are ambiguous. In some cases, addressing non-IID-normal properties underlying the stock return data reverses the standard test outcome of predictability whilst in other cases, the simulation results are consistent with standard tests. This is in contrast to the results obtained in previous studies such as the ones by Brock, Lakonishok and LeBaron (1992) and Bessembinder and Chan (1995), who find that simulation results are similar to standard tests.

However, like Brock, Lakonishok and LeBaron (1992), we find that the standard test outcome of predictability is affected in a higher number of cases when we use GARCH(1,1) and EGARCH(1,1) simulations compared to random walk and AR(1) simulations. Hence, in this paper, we also find that the significant results obtained with the random walk and AR(1) simulations, but which are later insignificant with the GARCH(1,1) and EGARCH(1,1) simulations, are due to the ignored presence of time-varying conditional variances in the data. We find no differences in the results from tests using GARCH(1,1) and EGARCH(1,1) simulations, which suggests that asymmetric responses in the conditional variance to past positive and negative returns does not affect the standard test outcome of technical rules.

6.0 Conclusions

This paper presents the results of testing the application of three types of simple technical trading rules – the VMA, FMA and TRB rules – in the ASX from 1980 January 01 through 2002 December 31. We conduct the empirical analysis in two stages. In the first stage, we use standard tests to determine if technical rules generate abnormal returns by comparing technical trading returns against the buy-and-hold equivalent. Results show some evidence of predictability in the full sample, especially with the application of FMA and TRB rules. However, sub-sample tests indicate the loss of predictive power by all three types of technical rules over time, especially from 1991 onwards. In fact, the loss of predictive power experienced by FMA and TRB rules is so dramatic that they actually generate significantly negative Buy-Sell spreads in the most recent sub-sample! This has important implications for the EMH, since it implies that the ASX grew increasingly informationally efficient over the sample period and to such an extent that technical trading rules are no longer useful forecasting tools for the investor since about 10 years ago.

However, we acknowledge that results from standard tests do not provide a complete picture on the performance of technical trading rules. Standard tests assume data is IID-normal, whilst stock returns are known to exhibit non-IID-normal properties such as leptokurtosis, time-varying means, serial correlation and heteroskedasticity. One problem that can arise from this inconsistency is that standard tests find technical rules significant even when technical rules do not in fact possess forecasting power simply because standard *t*-ratios are unable to address the non-IID-normal properties underlying empirical data. For the same reason, it is also possible for standard tests to find insignificant technical rules when technical rules actually possess forecasting power. We therefore conduct a second stage of tests based on a procedure that employs bootstrap methods to generate empirical distributions simulated under four models of stock prices – the random walk with drift, AR(1), GARCH(1,1) and EGARCH(1,1) models.

We find our simulation results different depending on which type of technical rule is under investigation. Simulation results for VMA rules support standard tests and indicate that the standard test outcome of predictability is unaffected by the non-IID-normal properties characterized by the four models. Simulation results for FMA rules, on the other hand, are ambiguous. Simulation results support standard tests for some FMA rules whilst in other cases, the standard outcome of predictability is reversed by addressing non-IID-normal properties underlying the empirical data. For TRB rules, the standard test outcome of predictability is reversed in most cases when the random walk and AR(1) simulations are used and in all cases when the GARCH(1,1) and EGARCH(1,1) simulations are used. This is in contrast to the findings of previous studies, which typically find simulation results supporting standard tests and that technical rules possess predictive ability. Instead, our findings indicate that it is possible to reverse the standard test outcome of predictability for certain types of technical rules by addressing non-IID-normal properties underlying data.

Overall, this study finds that the simulations of various stochastic models of stock returns diminish but do not virtually eliminate the abnormal returns generated by trading rules in the ASX. This suggests that the returns-generating process of ASX stocks is probably more complicated than suggested by the four linear models examined and that certain types of technical rules pick up other properties in the data. The evaluation of technical trading returns using other more complicated models of stock returns is left for further research.

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