A UNIFIED TRADING STRATEGY COMBINING TECHNICAL TRADING RULES AND TIME SERIES ECONOMETRICS

DANELEE VAN DYK*

Abstract
This study develops a comprehensive stock market trading model, which is based on a combination of technical trading rules and time series forecasts. The specification and success of such a model is dependent on the different predictable components of each method. Firstly, validating the use of technical trading analysis for stock price forecasting is that trends tend to persist. Secondly, stock market characteristics, such as volatility clusters, can be captured by GARCH processes. From the combined model buy (sell) signals will be generated such that by taking long positions on buy signals returns will be enhanced, while predicting periods for traders to exit the market in favour of alternative higher yielding investments when sell signals are emitted. Applied to daily data over a ten year period the combined model outperforms the technical and econometric model predictions, which can largely be attributed to low-order serial correlation in returns.

J.E.L. Classification Codes: C220, C530, G100. Time Series Models, Forecasting & *Other Model Applications, General Financial Markets*

1. INTRODUCTION

There has been a longstanding segregation between two schools of thought, the technical analysts, or chartists, and fundamentalists. Fundamental analysis involves evaluating a stock by attempting to measure its intrinsic value, assessing broad-based indicators ranging from economic and industry conditions to the financial environment and management of companies. In contrast, technical analysis ignores fundamentals altogether, with trading purely based on the price history of a stock. The use of technical trading rules remains widespread in financial markets, some relying extensively on it, but most require a good deal of subjective judgment in their application.

The movement of the stock market as a whole, as represented by its benchmark index, is driven by three types of forces: business dynamics, mass psychological dynamics, and news impacts. The fusion of these dynamic components into a system of cycles serves to confirm the rather complex nature of financial markets, let alone the investor's decision making process under these circumstances. In a dynamic investment environment where

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the only constant is change, market participants are faced with numerous challenges whereby the need for instantaneous decision making could have far-reaching implications for financial profitability. Therefore the ability analyse information in a timely manner is one of the most important factors in exploiting attractive investment opportunities in financial markets. Taking advantage of opportunities could be costly, thus emphasising the need for optimal decision making in a given timeframe and within the limits of available resources. Investors have numerous tools at their disposal, such as fundamental, technical, and quantitative tools and methods. Literature confirms that technical buy and sell signals have proven to be value-added indicators for good decision making. It is herein expected that trading strategies combining technical analysis and time series forecasts are superior to employing them individually.

In essence, previous research studies, such as Brock, Lakonishok and LeBaron (1992) and Levich and Thomas (1993), focused on the performance of technical strategies and econometric time series forecasts in isolation. Such an approach is unsatisfactory, as these different techniques capture different predictable components. The need for combinations of different techniques has its origins in the market being driven by various forces, each of these forming a joint impact leading to changes in price. The aim of this study is to combine technical analysis and quantitative analysis into a unified theory, a major step in this convergence, therefore doing away with the single-minded approach to decision making.

This study attempts to examine new ways of combining information pertaining to stock market data, such that a trading system can be derived from technical trading rules and quantitative econometric models. Each model focuses on different aspects of price trends, such as structural changes and volatility as well as the behavioural aspects and psychology behind market participants' actions. The general goal is to provide an innovative model that will generate buy (sell) signals pertaining to the stock prices, by merging traditional technical rules, such as moving averages, and econometric models renowned for capturing stock market volatility, i.e. Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models. More specifically, buy and sell signals will first be generated using technical trading rules, such as moving averages and filter rules, which normally form the basis of more advanced schemes. Ten technical trading rules characterised by different combinations of short and long periods will be generated over the full sample period and three subsample periods. Furthermore, these rules' ability to capture the predictability of asset returns will be applied and tested. The significance of the returns generated by each trading rule will be evaluated by the student t-distribution.

As stated in this section, the purpose of this study is to examine the predictability of a stock market index by combining technical analysis and quantitative econometric forecasting techniques in an attempt to become more cost efficient, thus enhancing profitability. The second section deals with a review of supporting literature relevant to this topic. Data requisites, methods and procedures of the study are presented in the third section, followed by the results of the empirical investigation and interpretation in section four. The final section of the study summarises key findings and provides suggestions for further research.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

The purpose of this section is to serve as a literature overview of the profitability and the predictive power of technical analysis. According to Park and Irwin (2004), among a total of 92 modern studies, 63% of the studies found positive results regarding technical trading strategies, while negative results were documented by 26% of the studies and 11% documented mixed findings. Based on study methodologies and testing procedures, seven groups are identified and summarised in Table 1, followed by a brief overview of each study. For a more detailed review of the results of these respective studies as well as their recorded profitabilities, consult Park and Irwin (2004).

Table 1: Summary of modern studies (1988 – 2004) on technical analysis

Distinctive features	*General findings*
Standard (23)* *Pioneered by: Lukac, Brorsen & Irwin (1988)*	
Profitability of technical trading rules using parameter optimisation, out-of-sample verification and statistical tests for trading profits. Transaction costs and risk were also included.	Technical trading rules such as moving averages and closed channels, yielded profits in speculative markets. Annual net returns ranged from 3.5% to 5.4%. Some did not explicitly address data snooping problems.
Model-based bootstrap (21)* *Pioneered by: Brock, Lakonishok & LeBaron (1992)*	
Model-based bootstrap methods used for statistical tests. Included risk adjustment. No parameter optimisation and out-of-sample tests conducted.	Technical trading rules, such as moving averages and trading range break were profitable in several emerging markets, not developed markets. Annual net returns ranged between 18.1% - 32.1%
Genetic programming (11)* *Pioneered by: Allen & Karjalainen (1999)*	
Trading rules optimised by genetic programming techniques. Included all criteria such as transaction costs, risk adjustment, out-of-sample and statistical tests. Data snooping also addressed.	Attempted to avoid data snooping problems by testing ex ante optimised trading rules. More successful in foreign exchange markets. Annual net returns ranged between 1.7% and 8.3%.
Reality check (3)* *Pioneered by: Sullivan, Timmerman & White (1999)*	
White's Reality Check Bootstrap methodology and statistical tests. Incorporated all of the above criteria except transaction costs.	Technical trading rules might be profitable in the stock market until mid-80s but not thereafter. Annual mean return of only 2.8%, but could increase to 12.2%.
Chart patterns (11)* *Pioneered by: Chang & Osler (1999)*	
Use recognition algorithms for chart patterns, such as head-and-shoulders. Criteria included transaction costs, risk adjustment and statistical tests.	Some chart patterns might have been profitable in stock markets and foreign exchange markets. Results depend on patterns, markets and sample periods. Annual net returns of about 13% - 19%.
Nonlinear (7)* *Pioneered by: Gençay (1998a)*	
Use nearest neighbours and/or feed-forward network regressions to generate trading signals. Data snooping was not addressed.	Technical trading rules possessed profitability or predictability in both stock and foreign exchange markets. Annual net returns of up to 35% were reported.
Others (16)* *Pioneered by: Neely (1997)*	
Most studies in this category lack trading rule optimisation and out-of-sample tests and do not address data snooping problems. Transaction costs, statistical tests and risk adjustment generally featured in these models.	Trading rules profitable in stock and foreign exchange markets. Positive net returns between 1.0% and 26.6%. Data snooping might have been reasons for these successful findings.

**Indicates number of studies*
Source: Adapted from Park & Irwin, 2004

Model-based bootstrap studies apply the bootstrap methodology to test the statistical significance of trading profits, by performing a joint test of significance for different trading rules by constructing bootstrap distributions (Park & Irwin, 2004:23). The standard statistical analysis is extended through the use of bootstrap techniques. The results of the research are consistent with the popular belief that technical trading rules have predictive power and outperform some other techniques (Tan & Dihardjo, 1999:1).

Genetic programming, introduced by Koza (1992), is a computer-intensive search procedure based on the Darwinian principle of survival of the fittest (Park & Irwin, 2004:33). In this procedure, a computer randomly generates a set of potential solutions for a specific problem and then allows them to evolve over many successive generations under a given performance criterion. Solution candidates (e.g. technical trading rules) that satisfy the fitness criterion are likely to reproduce, while ones that fail to meet the criterion are likely be replaced. Neely, Weller and Dittmar (1997) found strong evidence of economically significant out-of-sample excess returns to technical trading rules for six exchange rates over the period 1981-1995.

Unlike genetic programming, the effects of data snooping in the traditional framework of ex post and in-sample searches for profitable trading rules can be assessed by the *Bootstrap Reality Check* methodology. This statistical procedure developed by White (2000) involves testing a null hypothesis that the best trading rule performs no better than a benchmark strategy. The best rule is then searched by applying a performance measure to the full set of trading rules, and a desired p-value can be obtained from comparing the performance of the best trading rule to approximations of the asymptotic distribution of the performance measure (Park and Irwin, 2004:37).

In the literature, a more common study of technical analysis takes the form of *chart pattern* studies, testing the profitability or forecasting ability of visual chart patterns widely used by practitioners. Famous chart patterns whose names are normally derived from their shapes represent flags, pennants, saucers, triangles, diamonds and head-and-shoulders. Levy (1971:322) studied thirty two chart patterns to test their predictive significance, finding discouraging evidence that none of these patterns generated profits greater than average purchase or short-sale opportunities. However, a more rigorous study by Chang and Osler (1999) on the predictive significance of the head-and-shoulders pattern using daily data for 6 currencies, between 1973 to 1994, yielded supportive evidence on the predictability of this trading rule for the Deutsche mark and the Japanese yen.

Nonlinear studies attempted to directly measure the profitability of a trading rule derived from a nonlinear model, such as feed-forward networks or the nearest neighbour's regressions. They also attempt to evaluate the nonlinear predictability of asset returns by incorporating past trading signals from simple technical trading rules (e.g. moving averages).

Between 1990 and 2005 many *new approaches* to financial modelling have emerged, breathing fresh air into the field. Examples listed by Leigh, Modani, Purvis and Roberts (2002:154), all of which resoundingly reject the joint hypothesis of rationality and risk neutrality i.e. the efficient market hypothesis, include fuzzy expert systems combining several sources of information (Lee & Kim, 1995); embedding technical analysis into neural networks based trading systems (Chenoweth & Obradovic, 1996); neural networks learning from knowledge of real world events and past history (Kohara et al., 1997) and (Gençay 1998) respectively; and decision support systems with influence diagrams (Poh, 2000).

Overall, the abovementioned research articles serve to confirm that there is some shortage of studies combining technical analysis predictions of stock price movements with that of more sophisticated econometric models. Refer to Brock et al (1992), Levich and Thomas (1993) and Gençay (1998) for analyses that add value to the combined approach of technical trading and econometrics.

Of particular inspiration to the work of this study, is the empirical investigation documented by Fang and Xu (2002) on the predictability of asset returns, an approach combining technical analysis and time series forecasts. In their study, it is demonstrated how trading strategies can be developed by incorporating technical analysis and time series forecasts in a unified model. The paper distinguishes itself from the aforementioned studies, in that optimal results are obtained by joint simulation, as technical trading rules and time series models are able to identify different predictable components. The work done by Fang and Xu draws extensively from ideas generated by Brock et al (1992) amongst others, albeit that their approach, to the best of the author's knowledge, is one of the first studies of convergence in technical trading rules and time series forecasts.

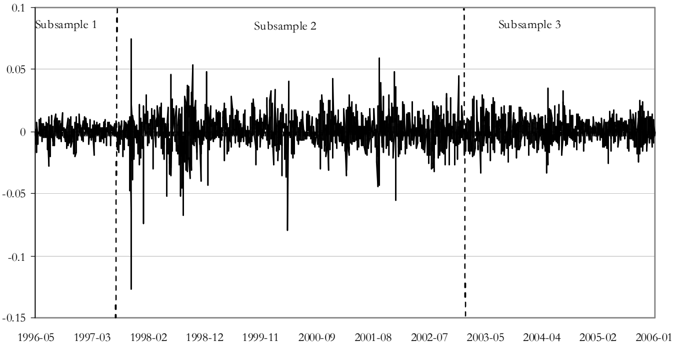
3. PRELIMENARY DATA ANALYSIS AND METHODOLOGY

This section discusses the techniques used to develop the technical trading rules and the time series forecasting models. The combination of these models, if successful, will allow investors to optimise their trading system by making profitable trading decisions based on different predictable components captured by these models.

a) Data

The database is composed of 2 428 observations (from 3 March 1996 to 16 January 2006), represented by the daily closing prices of the Africa All Share Index (ALSI) of the Johannesburg Securities Exchange. This index is sufficiently representative of the South African stock market since it accounts for more than 99% of total trading volume. Furthermore, this index is commonly used to assess the state of the economy and also serves as the basis of some investable products, as shares can be traded in a fund that holds stocks in the ALSI. Besides the full sample set, results are also presented for three subsamples: 3 March 1996 to 14 October 1997; 15 October 1997 to 17 December 2002; and 18 December 2002 to 16 January 2006. As depicted in Figure 1, the three samples, respectively, are characteristic of low, high and medium levels of volatility.

Figure 1: Evidence of volatility clustering in the returns of the All Share Index



b) *Summary statistics*

Table 2 contains the summary of statistical results for the entire sample and three subsamples of the ALSI. Returns are calculated as daily changes in logarithms of the share index and thus exclude dividend yields. Volatility is the most pronounced in the second sample, as this sample contains the stock market collapse of 41% and 24% during 4 May to 3 September 1998 and 24 May to 5 August 2002 respectively, while also including the currency crisis in 2001/02. Furthermore, non-normality in returns over the full sample period is manifested as expected owing to a high degree of kurtosis and skewness. A reduction in kurtosis is observed across all subsamples.

Table 2: Summary statistics for daily returns

Statistics	*Full sample*	*Subset 1*	*Subset 2*	*Subset 3*
Data count	2427	365	1292	770
Minimum	-0.1269	-0.0277	-0.1269	-0.0336
Maximum	0.0742	0.0149	0.0742	0.0345
Average	0.0004	7.55E-05	0.0003	0.0009
Std. deviation	0.0121	0.0064	0.0144	0.0096
Kurtosis	12.1271	4.3111	10.6882	3.4913
Skewness	-0.8012	-0.6955	-0.8581	0.0312

There is significant first-order autocorrelation over the full period, as evidenced by the partial autocorrelation coefficient (0.115), which is strongly significant at the 1% level. The first-order serial correlation coefficients for the three subperiods (0.145; 0.124; 0.073) are significant at the 1% level, with the exception of the third subsample which is only significant at the 5% level. This indicates that the ALSI is to an extent predictable on the basis of past price history. The gradual decay in the partial autocorrelation coefficients after a one day lag is also suggestive that the underlying data generating process for the ALSI might be characterised as AR(1).

c) *Moving averages and technical trading rules*

i. *Theoretical considerations*

Analysts and investment advisors have long searched for investment tools that would either furnish predictive probabilities for future security price movements, or would aid in minimising losses. One such tool, often recommended by market practitioners is the moving average. An integral part of the technical hypothesis of stock price movements is that trends tend to persist. Simply stated, this belief holds that when a security price rises or falls "in a decisive manner", the probability that the rise or fall will continue for some time exceeds 0.5 (James, 1968:317) and (Fang & Xu, 2002:5).

Frequently in the literature, a moving average rule is coupled with a tactic designed to delay action and to reduce the number of transactions (especially "whiplash" transactions) which may occur if the security fluctuates within a narrow price range for any appreciable time period (James, 1968:319). This filter rule gives a buy (sell) signal when the short moving average penetrates the long moving average line on the upside (downside) by at least x%. Thus, if the short moving average (M_S) is inside the band, no signal is generated. Generally, the profitability results are closely linked to the number of trades the system generates. Large numbers of trade may cause overtrading, reducing the profit by substantial amounts mainly on account of high transaction and funding costs.

This study will focus on the unweighted moving average dual-crossover trading rule. As stated by Bredin and Hyde (2002:8), while the exponentially weighted moving average model captures volatility clustering, a richer description of behaviour is provided by GARCH models proposed by Bollerslev (1986). Alexander (2001) also suggests that long-term forecasts are more realistic when generated by GARCH models as opposed to exponentially weighted moving average models. For this reason, an optimized trading strategy is generated by combining GARCH models, which effectively captures and forecasts volatility, and technical trading rules which depict the direction of the market.

ii. *Buy-and-sell trading rules based on moving averages*

The technical trading rule (S, L, f) based on the unweighted moving average M_S , M_L and the filter band f, with moving average window lengths $L > S \geq 1$, is defined as follows:

Table 3: Technical trading rules: buy and sell signals

Buy signals (τ_i^B, $i \geq 1$)	**Sell signals (τ_i^S, $i \geq 1$)**
$\tau_i^B \equiv inf\{t{:}t > \tau^B_{i-1}, M_S[x_t] - M_L[x_t] > fx_{t-1}\}$	$\tau_i^S \equiv inf\{t{:}t > \tau^S_{i-1}, M_L[x_t] - M_S[x_t] > fx_{t-1}\}$

Source: Fang & Xu (2002)

Table 3 depicts the sequential trading rules which classify all trading sessions (t) into buy, sell or no action, such that a buy signal is generated when the short moving average cuts above the long moving average from below by a percentage change larger than the band f. Alternatively, if the short moving average falls below the long moving average from above by a percentage change larger than f, a sell signal is given. If the short moving average falls between the bands, no trading signal is generated. The band therefore also serves as a cost saving mechanism for minimising unnecessary trades brought about by volatility in share prices.

In addition, this study attempts to incorporate the profile of a risk seeking trader who is expected to trade even on days when no action is required owing to the violation of the above constraint. Recall, though, that no trading action would be the result of the failure of the short moving average to penetrate the long moving average by more than 1% of the previous session's closing price. More specifically, the trader is expected to maintain an open position, for example a long position, instead of exiting the current position even if the following signal requires no trading action to be taken on that day. Thus the trader will only exit the existing trade on a sell signal. In this manner, risk is assumed by the probability of the trader incurring a revenue loss, as the spread between the short- and long moving average narrows, i.e. the trading conditions listed above are violated. The payoff associated with this strategy comprises fewer transactions, which reduce operation costs.

Table 4 illustrates the methodology behind the buy and sell returns as well as their associated t-statistics.

Table 4: Formulation of buy and sell returns and their significance tests

Buy returns	Sell returns
$y_h = ln(x_{t+h}) - ln x_t$	$y_h = -(ln(x_{t+h}) - ln x_t)$
t-statistic	**t-statistic**
$(\mu_B - \mu)/(\sigma^2/N + \sigma^2/N_B)^{1/2}$	$(\mu_S - \mu)/(\sigma^2/N + \sigma^2/N_S)^{1/2}$
For the buy-sell t-statistic	
$(\mu_S - \mu_S)/(\sigma^2/N_B + \sigma^2/N_S)^{1/2}$	

Where:
μ_B: mean return conditional on a buy or sell signal
μ: unconditional mean
N: unconditional number of observations
N_B: number of buy or sell signals
σ^2: the estimated variance for the entire sample

Source: Brock et al (1992), Author

In effect, the three t-statistics are used to test whether buy (sell) signals are no different from the unconditional mean and whether the difference between buy and sell returns is no different from the unconditional mean. The point to be made is that, should technical analysis not have any power to forecast price movements, then returns on buy days when the rules emit buy signals should not differ appreciably from returns on days when the rules emit sell signals. This should be reflected by insignificant t-statistics. A shortcoming of this testing procedure is that the reported t-statistics are only indicative of significance, since the actual distribution of the reported statistics is unknown, given the manifest of non-normality of the return distribution for the ALSI. The t-statistics essentially assume independent, stationary and asymptotically normal distributions.

c) *GARCH time series trading rules*

The second leg of the trading model relies on time series forecasts for the generation of a sequential trading system. It is well-known that market data tend to have volatility clustering identified by periods of high volatility which gradually subsides. GARCH models are popular means of modelling market volatility. The autoregressive (AR) models with GARCH components make the variance of the residuals predictable and successfully capture the stylized facts of the conditional second moment of returns, such as thick tails and volatility clustering (Fang & Xu, 2002:9). The documented successes of daily GARCH forecasts form the basis from which potentially significant buy and sell signals are formulated. Trading rules based on a one-period forecast generated by the GARCH model is denoted in the following table:

Table 5: Trading rules of GARCH generated time series

Buy signals (τ_i^B, i ≥1)	Sell signals (τ_i^S, i ≥1)
$\tau_i^B \equiv E(y_t \mid I_{t-1}) > \delta$	$\tau_i^S \equiv E(y_t \mid I_{t-1}) < -\delta$

Source: Fang & Xu (2002)

As stated by Fang and Xu (2002:9), a trading rule is generated in the current period (*t-1*) if the forecast return in period *t* is either above or below a constant, δ, based on the information set I_{t-1}, where I_t depends on the model specification of y_t (log difference of the index). Furthermore, the constant is a reasonable proxy for trading costs and therefore takes on non-zero values. However, in the absence of convincing reasons to choose a specific level, it is simply taken to be zero. Thus, a buy (sell) signal is generated in *t-1* if the GARCH forecast of return in time *t* is positive (negative).

d) Combined trading strategies

The third facet of the trading model entails the simulation of the technical trading rules arising from the two quantitative procedures outlined above. In formulating the combined trading rule, it can be logically construed that a buy (sell) signal is generated at time *t-1* if both the technical trading rule and time series model emit a buy (sell) signal, based on the information set in period *t-1*. The trading strategy combining technical trading rules and time series forecasts is specially designed to produce fewer buy and sell signals. Hence, a lower number of transactions potentially increases the profitability of the combined trading mechanism in a costly trading environment.

4. EMPIRICAL RESULTS AND INTERPRETATION

This section is devoted to the presentation of the results in accordance with the methodology discussed in the preceding section. The findings are partitioned into three categories, namely technical trading rules, time series forecasts and the simulation of these two models into a combined trading strategy. For comparative purposes, the results are presented for both the full sample and subperiods, with the aim of the latter providing the degree of robustness analysis of the estimated trading strategies. However, for the purpose of conserving space, the detail of each individual trading rule in the subperiods has been omitted only to present the averages across buy and sell periods.

a) The moving average strategy

Results from the moving average dual-crossover trading rules are presented in Table 6, which is designed to replicate returns (excluding trading costs) where the trader buys when the short moving average penetrates the long moving average from below and maintains the position until the former penetrates the latter from above, while also adhering to the filter rule. The trader either moves out of the market or sells short on the occurrence of the sell signal.

While not indicated in Table 6, the filter rule holds the advantage of reducing the number of trades (also referred to as whiplash trades) by up to 54% relative to trading rules excluding a filter band, i.e. a zero percentage rule. More significantly, the introduction of the filter band increased the spread between the buy and sell returns across all moving average combinations and sample periods, as noted by the difference in the buy-sell spreads of one and two percentage filter rules.

The columns labelled *N(buy)* and *N(sell)* are the total number of buy and sell days respectively, whilst the total number of long and short positions (each position is taken as one trade) is depicted by *N(trades)*. In each trading strategy the respective mean buy and sell returns are denoted by *Buy* and *Sell* with the upshot of the last column, *Buy – Sell*, measuring the spread between the returns. The t-statistics alluded to in the previous section are presented in parentheses.

Table 6: Standard test results for the moving average rules

Trading statistics moving averages: full sample

Trading rule	N(buy)	N(sell)	N(trades)	Buy	Sell	Buy-Sell
(1,50,1)	1 339	749	61	**0.0361** *(16.33)***	**0.0050** *(2.08)**	**0.0310** *(10.04)***
(1,50,2)	164	142	71	**0.0380** *(18.26)***	**0.0056** *(2.53)**	**0.0324** *(11.31)***
(1,150,1)	1 508	716	23	**0.0781** *(22.23)***	**-0.0097** *(-2.79)***	**0.0879** *(17.43)***
(1,150,2)	1 508	666	23	**0.0710** *(20.19)***	**-0.0208** *(-5.82)***	**0.0918** *(18.21)***
(5,150,1)	1 507	727	17	**0.1071** *(26.44)***	**-0.0138** *(-3.33)***	**0.1209** *(20.60)***
(5,150,2)	1 507	666	17	**0.0989** *(24.42)***	**-0.0238** *(-5.67)***	**0.1227** *(20.92)***
(2,200,1)	1 479	636	34	**0.0448** *(15.08)***	**-0.0216** *(-7.49)***	**0.0663** *(16.01)***
(2,200,2)	1 479	565	24	**0.0595** *(16.90)***	**-0.0351** *(-10.16)***	**0.0946** *(19.19)***
(5,200,1)	1 475	637	22	**0.0551** *(14.97)***	**-0.0464** *(-12.83)***	**0.1015** *(19.71)***
(5,200,2)	1 475	547	20	**0.0391** *(10.10)***	**-0.0742** *(-19.50)***	**0.1132** *(20.97)***
Average return				**0.0628**	**-0.0235**	**0.0862**
Average returns across subperiods						
3 March 1996 – 14 October 1997				**0.0078**	**-0.0407**	**0.0413**
15 October 1997 – 17 December 2002				**0.0237**	**-0.0228**	**0.0465**
18 December 2002 – 16 January 2006				**0.2418**	**-0.0099**	**0.2517**

**(**) Significant at 5% (1%) using a two-tailed test, with a critical value of 1.96 (2.57)*

Of noteworthy importance is the tremendous return posted in the third subsample owing to a sustained upswing in returns which were captured by long trade positions. As such there were several trading rules that would have afforded the investor with an average buy return in excess of 30%, while all rules have yielded an average buy return of 24.18% over this period. The first subsample generated the weakest results with an average return of 0.78% across all buy strategies. The second subsample period yielded average buy returns of 2.37%. On average, moving average trading rules would have rewarded the investor with a 6.28% return during the total trading period.

For the sell returns, the average return is a negative 2.35%, with only two trading rules significant at the 5% significance level. Negative average sell returns were recorded across all but one of the trading rules during the entire sample period. These negative returns are especially noteworthy and cannot be explained by various seasonalities, since they have occurred over approximately 30% of the trading days. Furthermore, negative sell returns were also confirmed in previous studies pioneered by Brock et al. (1992:1740). In their analysis, the predictability of negative returns over such a large fraction of days is possibly explained either by changes in expected returns that result from an equilibrium model, or market inefficiency. However, it is difficult to distinguish between these alternative explanations and it is hard to imagine an equilibrium model that predicts negative returns over such a large time period. Importantly, the last column lists the measure of the performance of the various trading statistics, in that it assesses the predictive power of technical analysis. The overall predictability of returns is very much in line with results from previous literature studies.

b) Time series forecasts

i. Estimation procedure and results

This section presents and discusses the results of the GARCH model specification, with specific reference to the trading rule and forecasting generation procedures. The suitability of this model in capturing various features of observed financial time series, especially volatility clustering and fat-tailed distributions, is well documented (Neely & Weller, 2002; Cecconi, Gallo & Lombardi, 2002) yet falls beyond the scope of this paper. In essence, volatility can be measured in a variety of ways; however, this study's primary measure of volatility is filtered out of the benchmark GARCH (1, 1) model. This model is fitted to the daily index returns, measured by the differences in daily logarithms, over the entire sample period as well as three subsample periods.

In order to gain some insight on the characteristics of the series, it is opportune to evaluate several descriptive statistics. As is customary in financial time series, the unit root hypothesis is tested by means of the Augmented Dickey Filler test. The ADF statistics are presented in Table 7.

Table 7: Stationarity test: ADF statistic

Variable	*ADF statistic (level)*	*Critical value 5%*	*ADF statistic (first difference)*	*Critical value 5%*
Full Sample	-1.940*	-2.862	-44.910	-2.862
Subset 1	-1.765*	-2.869	-16.509	-2.869
Subset 2	-1.201*	-2.864	-31.834	-2.864
Subset 3	1.903*	-2.865	-26.677	-2.865

**nonstationary and contains unit root at level*

Working with log differences, i.e. the approximation of daily returns, is warranted by the unit root results. The hypothesis of a normal distribution of ALSI returns is also rejected; a common occurrence in most daily financial time series. After numerous trial and error estimations, the modelling strategy for the conditional mean equation is based on an AR(1) specification; which is appropriately selected by evaluation of significant t-statistics and a small Schwarz and Akaike Information Criterion. The residuals are indicative of a white noise process. The forecasting power of these trial estimations were evaluated by the lowest Theil inequality statistic and the root mean square error, while a measure of the covariance proportion was also examined. Following the joint consideration of all the abovementioned criteria, the AR(1) specification provided superior forecasting power on an in-sample and out-of-sample basis. The estimation results together with the error variance diagnostics are reported in Table 8.

Table 8: Parameter estimates for time series specification

AR(1)-GARCH(1,1) — *mean equation:* $y_t = \mu + \xi y_{t-1} + \varepsilon_t$ *variance equation:* $\sigma^2 = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$

Where : y_t – log returns; ω – GARCH constant, > 0;
α – GARCH error coefficient, > 0;
ε^2_{t-1} – ARCH term, i.i.d# with mean 0 and variance 1;
β – GARCH lag coefficient, >0; σ^2_{t-1} – GARCH term

	μ	ξ	ω	α	β
Full sample	0.0008	0.1354	2.1E-06	0.11	0.88
				*(14.94)***	*(144.15)***
Subset 1	0.0001	0.1583	5.1E-06	0.06	0.81
		*(2.69)***		*(1.96)**	*(7.69)***
Subset 2	0.0009	0.1543	1.6E-05	0.16	0.76
		*(4.89)***		*(8.93)***	*(28.02)***
Subset 3	0.0011	0.0792	1.4E-05	0.07	0.92
		*(2.04)**		*(3.54)***	*(42.27)***

 # independently and identically normally distributed
**(**) significant at the 5% (1%) significance level*

The GARCH model for the entire sample period, estimated by maximum likelihood, exhibits the customary order of magnitude for α of around 0.1 and β at approximately 0.88. The autoregressive root that dominates the persistence of volatility, i.e. $\alpha + \beta$, is close to one, with the exception of subset one which suggests that volatility dies out fairly quickly (a brisk decline in the autocorrelations of σ^2.) Furthermore, the importance of this finding yields the returns process stationary. Only in this case will GARCH volatility term structures converge to a long term mean level of volatility determined by $\sigma^2 = \omega / (1 - \alpha - \beta)$ (Alexander, 2001:75).

As the model parameter estimates, especially the constant, i.e. ω, are normally sensitive to the data used, the choice of the sample period will affect the current volatility forecasts. According to Alexander (2001:75), long term volatility forecasts will be influenced by the inclusion of stress events in the historic data. It is therefore possible that higher volatility around the 1997 mini-market crash, emerging market crisis in 1998 and the collapse of the rand during 2001/02 could affect the general out-of-sample forecasts.

ii. Time series trading rules

Table 9 displays the results of the AR(1)-GARCH (1, 1) model. These results are reported to motivate the approach of the combined strategies, discussed in the following section. Importantly, the trading statistics are based on a static in-sample fit of the AR(1)-GARCH(1, 1) model, with a buy (sell) signal generated in *t-1* if the GARCH forecast of return in time *t* is positive (negative).

Table 9: Standard test results for the GARCH trading rules

Trading statistics GARCH-rule

Period	N(buy)	N(sell)	N(trades)	Buy	Sell	Buy-Sell
Full sample	1 764	662	832	**0.0115** *(17.30)***	**0.0004** *(0.01)*	**0.0111** *(13.24)***
Subset 1	221	143	91	**0.0035** *(3.37)***	**0.0023** *(2.24)**	**0.0012** *(0.87)*
Subset 2	896	396	476	**0.0036** *(3.29)***	**0.0035** *(3.19)***	**1E-04** *(0.08)*
Subset 3	712	58	265	**0.0115** *(11.91)***	**0.0004** *(-0.47)*	**0.0111** *(9.46)***
Average returns				**0.0062**	**0.0021**	**0.0041**

**(**) Significant at 5% (1%) using a two-tailed test, with a critical value of 1.96 (2.57)*

In contrast to the results presented in Table 6, the number of buy and sell trading days are significantly higher across the periods in review, while the number of trades required has also risen. This can in part be ascribed to the close fit generated by the GARCH model in predicting volatility and subsequent trading signals, while, as opposed to the technical trading model, every day is classified into a buy or sell day and does not allow for non active trading days as a result of a filter rule.

When analysing the respective buy and sell returns of the GARCH and technical trading rule simulations, a remarkable difference in average sell returns is evident. That is, in the GARCH simulation the sell signals generated positive returns across all subsamples, with the t-statistics only significant in the first and second subset, at the 1% and 5% level respectively. Although the buy returns arising from time series forecasts, on average, were fairly lower than the aggregated returns posted by the technical trading rules, they nevertheless remain significantly different from the unconditional mean return. A possible explanation could relate to the volatility engendered by the model specification, such that buy signals are reversed too soon to fully capitalize on a longer established trend. Moreover, it needs to be emphasised that trading signals based on a one-step forecast approach is not infallible.

The hypothesis that returns on buy signals match returns generated by sell signals, thus rendering the predictive power of the model frail, is firmly rejected over the entire period and third subset, based on a 1% significance level using a two-tailed test. These findings suggest that technical trading rules and time series forecasts capture different aspects of market predictability, so that strategies combining the two methods will enhance confidence from a trader's perspective, while possibly producing more favourable results.

c) Simulation of combined technical trading rules and time series forecasts

A weakness of financial studies of this genre is that there is no presumption that profitability or predictability which existed in the past will continue in the future. It is consequently necessary to not only prove that the study worked in the past, but equally important to demonstrate that it continued to work in the post sample environment. It is to this issue that attention was placed on rolling GARCH regressions in generating out-of-sample forecasts. In addition, rolling the regression window forward by one day and maintaining a fixed window length of historical data available at period *t*, allow for the model parameters to adjust over time, therefore guarding against over-fitting the model. It needs to be emphasised that this study's aim is only to generate a one-step forecast, hence problems related to the sensitivity of longer term forecasts to the data used are minimised. Previous studies listed by Fang and Xu (2002:13), that is, Fama and Macbeth (1973) and Foster and Nelson (1996) also studied rolling regressions to respectively estimate conditional betas and rolling sample variance estimators. Their central motivation for using only the most recent data was to allow the model parameters to change over time.

The ten combined trading strategies evaluated are based on the technical trading rules examined in Table 9 and the rolling AR(1)-GARCH(1,1) model, with the rolling window size equal to the length of the first subsample period. The empirical results based on out-of-sample forecasts are reported in Table 10.

Table 10: Results for strategies combining technical trading rules and time series forecasts

Trading statistics moving averages and GARCH: full sample

Trading rule	N(buy)	N(sell)	N(trades)	Buy	Sell	Buy-Sell
G_(1,50,1)	1 067	293	55	**0.0458** *(19.78)***	**0.0069** *(2.78)***	**0.0389** *(11.95)***
G_(1,50,2)	162	126	73	**0.0355** *(17.29)***	**0.0053** *(2.42)**	**0.0302** *(10.69)***
G_(1,150,1)	1 146	246	23	**0.0790** *(22.48)***	**-0.0121** *(-3.43)***	**0.0911** *(18.07)***
G_(1,150,2)	1 146	233	23	**0.0710** *(20.19)***	**-0.0208** *(-5.82)***	**0.0918** *(18.21)***
G_(5,150,1)	1 131	234	17	**0.0949** *(23.41)***	**-0.0284** *(-6.74)***	**0.1232** *(21.00)***
G_(5,150,2)	1 131	216	17	**0.0934** *(23.04)***	**-0.0301** *(-7.13)***	**0.1234** *(21.04)***
G_(2,200,1)	1 111	215	28	**0.0532** *(16.31)***	**-0.0278** *(-8.74)***	**0.0811** *(17.76)***
G_(2,200,2)	1 111	196	22	**0.0701** *(19.08)***	**-0.0343** *(-9.51)***	**0.1043** *(20.26)***
G_(5,200,1)	1 098	205	22	**0.0542** *(14.73)***	**-0.0490** *(-13.55)***	**0.1032** *(20.04)***
G_(5,200,2)	1 098	182	18	**0.0540** *(13.29)***	**-0.0720** *(-17.96)***	**0.1260** *(22.14)***
Average return				**0.06511**	**-0.02621**	**0.09133**
Average returns across subperiods						
3 March 1996 – 14 October 1997				**0.0067**	**-0.0433**	**0.0500**
15 October 1997 – 17 December 2002				**0.0243**	**-0.0227**	**0.0470**
18 December 2002 – 16 January 2006				**0.2410**	**-0.0130**	**0.2540**

**(**) Significant at 5% (1%) using a two-tailed test, with a critical value of 1.96 (2.576)*

From Table 10 it can be seen that over the full sample period the number of trades required from the combined model has reduced significantly relative to the trading strategies in isolation. Comparative analysis of buy returns between the unified and technical trade models indicates that there is an average improvement of 0.12% and 0.35% in buy returns of the combined trading rules with one and two percentage point filter rules respectively. Across the entire sample period, the total average buy returns of the combined model have been enhanced by 0.23% (6.51% vs. 6.28%). The combined model predicted greater losses stemming from short positions, with one and two percentage point filter rules on average predicting additional losses of 0.48% and 0.07% respectively. On an average basis, the trader will be 0.27% (-2.62% vs. -2.35%) worse off as a result of acting on sell signals based on the combined model over the full sample period.

The entries in the *Buy-Sell* column indicate that returns (excluding trading costs) are significantly different from zero, also supporting conclusions from previous literature studies on the predictability of technical trading rules. Furthermore, combined trading rules with a two percentage point filter band have amplified results over the entire sample period, verifying *a-priori* expectations for enhanced returns arising from the reduction in whiplash trades.

In addition, another positive factor that eradicates uncertainty, if any, over the sizeable improvements in returns, is rooted in evidence that larger average buy returns recorded by the combined trading strategy cannot be ascribed to an increase in the number of buy days. Comparisons between the number of days spent in long positions of technical trading and the combined trading models, illustrate an average reduction of 324 days in the latter model across each trading rule over the entire sample period. Evidence from the subsample sets confirms this inference. In similar fashion, fewer sell days in the combined model culminated in larger negative sell returns.

Overall, the combined trading strategies outperformed the corresponding technical trading and time series forecast rules across the full sample period. Aptly demonstrating the importance of introducing GARCH methodology into the combined model; GARCH forecasts only improved the buy returns in the second sample, as this period was characterised by the highest volatility.

5. CONCLUSION AND RECOMMENDATIONS

The primary objective of this study is to develop a comprehensive model pertaining to the stock market, such that a trading system can be developed based on a combination of technical trading rules and time series forecasts. The need for combinations of different techniques to forecasting has its origin in the market being driven by various forces, complicating the decision making process. On account of growing evidence on the predictability of asset returns documented by many studies, an approach to utilize the information of this study looks promising and may have practical value.

Motivated by the different aspects of predictability engendered by these models, an innovative trading model is developed that generates buy (sell) signals, by merging traditional technical rules with more advanced econometric specifications of stock market volatility, each of which generates their own respective buy (sell) signals. In this analysis trading rules with a filter bands are introduced with the benefit embodied in lower trading costs on account of the trader only entering the market when the stock price has changed by an amount larger than the percentage filter rule. This serves to cover the costs of trade while also helping to reduce false trades – a further cost minimising mechanism.

The robustness of the trading rules from the combined models across various sub-periods, characterised by different market conditions and volatility, supports the conclusions drawn from the full sample. The improved average spread between buy and sell returns for combined strategies render them superior relative to using these methods in isolation.

There are, however several caveats that weigh against the applied trading strategies. Firstly it is worth highlighting that the results are only suggestive given that the t-statistics do not follow a t-distribution, which assume independent, stationary and asymptotically normal distributions. These assumptions certainly do not characterise the returns from the ALSI series. Following Brock et al. (1992) this problem can be addressed by using bootstrap methods, which also facilitate a joint test across different trading rules that are not independent of each other.

Secondly, note that a significant range of moving averages 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 affect the trading schemes implied? Furthermore, there are always difficulties associated with trading the index portfolio in practice. In addition, trading rules introducing filter bands can be questioned, seeing that the best filter size can not be anticipated in advance, and it is also unlikely that an optimized in-sample filter would be appropriate in the future.

This analysis can be improved in several ways, for example implementing different time horizons of investment; introducing transaction costs; the implementation of non-synchronous trading; and the applications to various different stock or foreign exchange market averages. As explored by Fang and Xu (2002), investigation into the predictability of time series models can be extended beyond the use of a benchmark volatility model, to include variants of the GARCH family. With regard to the specification of technical trading rules, sensitivity to returns can be investigated by the implementation of non-synchronous trading (Fang & Xu, 2002; Bessembinder and Chan, 1998) due to growing consensus among financial economists that such trading induces spurious serial dependence in index returns.

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