The relationship between technical indicators and the market index

There are good reasons why investors need to look at the technical indicators to understand the movement of a stock index, say **MAURICE PEAT**, **MAX STEVENSON** and **DANIEL MARONEY**.

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Technical analysis is a general classification for a collection of techniques which use the past history of a security's price and its trading volume to forecast future price movement. The basis of this analysis is the belief that changes in supply and demand for a security can be determined through the analysis of market information.

These changes and the resultant price effects are assumed to reoccur over time, reflecting relative stability in the market's behaviour patterns. Technical analysis has a long history which can be traced back to the work of Dow in the late 1800s. Many of the techniques in use today have their genesis in this early analysis.

Academic interest in rule-based trading was stimulated by Alexander (1961) who examined the performance of a simple filter rule[1] applied to the Dow index. He found that the rule was capable of outperforming a naive buy-and-hold approach. This finding challenged the notion of market efficiency, which asserts that changes in asset prices are independent random events.

Buy and hold strategy

Market efficiency implies that trading rules should not be able to outperform a buy-and-hold strategy. Fama and Blume (1966) presented a critique of Alexander's result in which they argued that, after the inclusion of dividend payments and proper accounting for transaction costs, the buy-and-hold strategy outperformed the filter. The debate between proponents of technical analysis and market efficiency still continues along these lines.

The study by Brock, Lakonishok and LeBaron (1992) demonstrates that simple trading rules can generate returns that are higher than those from a random walk model. These results are confirmed in the work of Sullivan, Timmermann and White (1999) who test all combinations of 26 variations of four rules over 100 years of daily data. They use methods that correct for data snooping bias which is introduced when a data set is used repeatedly for model selection.

The results of these studies demonstrate that the use of rule-based trading strategies gives rise to significant and asymmetric returns. All of these studies vary from the recommended practice of technical analysis in that they use mechanical trading rules based on a single indicator, using search methods to optimize the parameters of the trading rule.

In this paper variables constructed from a number of technical indicators are used to evaluate the relationship between technical indicators and the Australian market index. A correlation analysis is carried out followed by test regressions that contain values of the constructed technical indicators as explanatory variables for the index.

To account for the nonstationarity of the index, a first difference of the index is used as the independent variable. The

[1] The basic idea of the rule is that an investor goes long when the price has risen by X% above the previous trough. Once the price subsequently falls X % below the previous peak, the investor sells and goes short.

regression analysis is in keeping with the practice of technical analysis by using a number of indicators to gauge the state of the market under study.

Variable definitions and empirical method

In technical trading there are two main classes of indicators. The first are trend-following indicators. This class includes moving averages and indicators constructed from the interactions of moving averages. These indicators are coincident or lagging indicators that turn after trends reverse. The second major class of indicators is oscillators. They are used to help in the identification of turning points in the price series. They include rate of change, momentum, stochastic and relative strength index indicators.

Mechanical trading rules can be constructed from these technical indicators. For example, a simple moving average buy(sell) rule involves the interaction of two averages[2].

One of the averages is calculated over a long period ($L_{m,\,t}$) where, typically, m is 50, 100 or 200 days. The second is calculated over a short period ($S_{l,\,t}$), for which l is usually 1, 2 or 5 days. The long average can be seen as an indicator of the direction of trend in the market.

If prices are above the long average and it is moving up then the market is in an up-trend state. If prices are below the long average and the average is moving down then the market is in a down-trend state. The short-term moving average indicates the direction of the short-term market sentiment, which may run with or against the long-term trend.

The interplay of short-term market sentiment and long-term market trends gives rise to the generation of trading signals using moving averages. If the short-term average comes from below and crosses above the long term average, then a buy is indicated as long as the price is above the cross-over point. If the short-term average comes from above and crosses below the long-term average, and the price is below the cross-over point, then a sell is indicated. This trading rule, with moving averages of various lengths, has been analysed extensively.

To test the explanatory ability of trend-following indicators that are based on moving averages, a variable that is observed each day needs to be formulated. As outlined above, buy and sell signals arise when the short and long moving averages cross, that is, when the distance between the short and long term averages falls to zero. Accordingly, we define a distance measure as $DSMA_{(l,\,m),t} = (S_{l,t} - L_{m,\,t})$.

When the short average is above the long average and $DSMA_{(l,\,m),t} > 0$, investors using the trading rule will hold long positions. Their expectation is that the index will be increasing. When $DSMA_{(l,\,m),t} < 0$, investors will be holding short positions with the associated expectation of negative market movements.

In this study, the length of the short-term moving average is set to one, while the length of the long-term moving average, m, is set to 5, 10, 50 and 100[3]. Another trend-following indicator is the Moving Average Convergence-Divergence (MACD) Line. This indicator is based on three exponential moving averages[4].

The Fast MACD Line is the difference between a 12-day and 26-day EMA. The Slow Signal Line is the 9-day EMA of the Fast MACD Line. A trading strategy based on the crossovers of the Fast MACD and Slow Signal Lines would indicate a long position when the former crosses above the latter. A short position is indicated when the Fast MACD Line crosses below the Slow Signal Line. The difference between the two indicators drives the generation of trading signals, so a measure known as the MACD-Histogram will be used in the analysis. We define the MACDH-Histogram[5] to be $MACDH_t$ = MACD $line_t$ - signal $line_t$.

Oscillators are used in technical analysis to identify the top or bottom of the market, that is, turning points. In this work we use the two simplest oscillators, momentum and rate-of-change. Both of these indicators measure the rate-of-change in a trend. They are leading indicators which show the progress of a trend. They tend to reach a peak or bottom before prices hit their high or low values. Momentum and rate-of-change indicators[6] compare today's price to a price selected a period of time ago. Momentum is calculated by subtracting a previous price from today's price, and is given by $M_{n,\,t} = P_t - P_{t-n}$

In this study we investigate the following differences, where n = 5, 7, 10. The rate-of-change indicator is calculated by dividing today's price by a past price. It follows that the rate-of-change indicator variable at time t, is

TABLE 1: **DESCRIPTION OF SUB-PERIODS WITHIN FULL SAMPLE PERIOD**

Period	Start	End	Observations
Full	2/1/90	15/12/04	3687
1	2/1/90	30/12/94	1238
2	3/1/95	30/12/99	1238
3	4/1/00	15/12/04	1211

[2] This type of trading rule is described in Murphy (1999) pg. 199-204.

[3] Most trend-following indicators are based on simple moving averages, in keeping with the previous literature. These averages are subject to spurious movements in the average induced by the entry and exit of large values in the calculation of the average. Many technical analysts use weighted or exponential moving averages rather than simple moving averages to correct for this problem.

[4] To calculate an Exponential Moving Average (EMA) of length *m*, first calculate a simple moving average of length *m* that serves as $EMA_{m,\,o}$. Then, using the smoothing coefficient, $K = 2/(m+1)$, and the current price, P_t, use the formula $EMA_{m,\,t} = Pt \times K + EMA_{m,\,t-1} \times (1 - K)$
The EMA has an attractive feature whereby it assigns the greatest weight to the last observation. Using this method differs from Simple Moving Averages as old data are assigned less weight in the progress of time, but are not dropped from the calculation. Also see Murphy (1999) pg 199.

[5] See Murphy (1999) p. 252-255.

[6] These indicators are described in Murphy (1999). Momentum on pg. 228. Rate of change on pg. 234.

given by $ROC_{n,\,t} = P_t / P_{t-n}$

The smoothed rate-of-change oscillator compares the values of an EMA, instead of prices, at two points of time $SROC_{(m,\,n),\,t} = EMA_{m,\,t} / EMA_{m,\,t-n}$

When momentum or the rate-of-change rises, the up-trend is accelerating. When it falls it shows that a down-trend is accelerating. Peaks and troughs of these indicators show turning points in the price series.

To statistically test the effectiveness of technical indicators, the constructed variables need to be used as explanatory variables in a model of the index. The statistical methods to be used in evaluating the technical indicators require stationarity of all the variables included in the model.

The construction of all of the variables based on technical indicators described above involves a stationarity inducing transformation. It is well known that stock index series are nonstationary, and that some transformation is required to induce stationarity. In this study a first difference, $PDIF_t = P_t - P_{t-1}$, of the series is used in the statistical analysis that follows.

Data description

The data consists of 3687 daily observations of the Australian Stock Exchange's All Ordinaries Index. The series starts in January, 1990, and runs through to December 2004. The analysis that follows is carried out over the full sample and over three sub-periods. The sub-periods are defined in Table 1.

The index data is nonstationary over the full sample and in each of the sub-periods. To induce stationarity the index was differenced, as is the standard practice for nonstationary series. The results of the stationarity tests are presented below in Table 2.

As is expected the results of the unit root tests show that the index is nonstationary over the full sample and each of the sub-periods. The results for the differenced series show that it is stationary in all periods under study and, therefore, suitable for use in the statistical analysis to follow.

The correlations of the technical indicators described above with the transformed index series in Table 3 below.

The first group of technical indicators, DSMA(l, m), are the distance between the short-term length, l, and long-term length, m, averages. For example, the first entry, DSMA1_5, is the difference between the current price and a simple moving average of length 5. The correlations between the first difference of the All Ordinaries Index with the various indicators are consistent across the full sample and the sub-periods. Indicators constructed from shorter averages have higher correlation with the differenced series than those based on longer averages. This finding is in keeping with the results of Sullivan, Timmermann and White (1999), who find that trading rules based on short-term averages are more profitable.

The second group are the momentum indicators. As was the case for the moving averages, the short length (5 day) momentum has the highest correlation with the differenced index. The MACD-Histogram indicator does not show a strong correlation with the transformed price series.

The final group consists of the rate-of-change momentum indicators. The ROC_n variables are the standard rate-of-change measures.

In the case of the differenced index, these indicators have higher correlations than the related SROC(m, n) indicators. Consistent with the other results for the differenced series, the short-term indicators have the highest correlations

These correlation results demonstrate that there is a statistical relationship between many of the indicators that are commonly used in technical analysis and the transformed index series. The next stage of the study is a multivariate analysis of the relationship between the technical indicators and the transformed index series.

Regression Results

The common practice in technical analysis is to look for buy and sell opportunities that are supported by a

TABLE 3: **CORRELATIONS OF TECHNICAL INDICATORS WITH THE DIFFERENCED INDEX**

Technical Indicators	Full	Period 3	Period 2	Period 1
DSMA1_5	0.7315	0.7302	0.7331	0.7323
DSMA1_10	0.5282	0.5308	0.5246	0.5303
DSMA1_50	0.2374	0.2350	0.2364	0.2481
DSMA1_100	0.1732	0.1734	0.1739	0.1785
M5	0.4463	0.4551	0.4339	0.4520
M7	0.3659	0.3735	0.3573	0.3656
M10	0.3038	0.3045	0.2978	0.3153
MACDH	0.1881	0.1883	0.1840	0.1964
ROC5	0.4268	0.4528	0.4304	0.4435
ROC7	0.3490	0.3713	0.3520	0.3620
ROC10	0.2906	0.3028	0.2939	0.3103
SROC5_10	0.1019	0.0944	0.0940	0.1384
SROC10_20	0.0335	0.0250	0.0206	0.0656
SROC12_25	0.0173	0.0141	-0.0033	0.0490

TABLE 2: **STATIONARITY TEST RESULTS**

	Period	Full		Period 1		Period 2		Period 3
Unit Root Tests	ADF Stat	p-val	ADF Stat	p-val	ADF Stat	p-val	ADF Stat	p-val
Index	0.05	0.96	-0.89	0.79	-0.91	0.78	-0.39	0.91
Differenced Index	-60.02	0.00	-31.36	0.00	-34.62	0.00	-35.93	0.00

number of indicators. All of the studies that have evaluated trading rules have used each indicator in isolation. The results of the previous section show correlations of up to 70% for some of the individual indicators.

In this section we explore the ability of a combination of contemporaneous technical indicators to explain the variation in the transformed price series. The results of forward stepwise regressions[7] are reported in Table 3. This approach introduces the technical indicators in the order of their explanatory ability, indicating the relative importance of the various indicators in each time period.

Table 4 contains the regression results for the full sample and the sub-periods.

In the case of the differenced index, the most important indicators are the short term (5 day) moving average and momentum indicators. All the technical indicators explain 66.3% of the variation in the differenced series, comparing favorably with less than 1% of the variation explained in an autoregressive regression. These results indicate that a combination of trend-following and momentum indicators is required to successfully explain movements in the index.

In all sub-periods the indicators that best explain the differenced index are the short term (5 day) moving average and momentum indicators.

The MACD-Histogram, another trend following indicator, is the third variable to enter in all differenced index regressions. The technical indicators explain between 66.8% and 69.5% of the variation in the differenced prices in the sub-period analysis.

The results for the differenced index tend to support the results of Sullivan, Timmermann and White (1999) who find that trading rules based on short-term indicators are profitable. In the regression analysis reported here, short-term indicators have the greatest explanatory power.

[7] The forward variable selection method calculates the statistic for C_p each augmented model. C_p is derived from following relation that incorporates the Akaike Information Criterion **(AIC), AIC** = δ ($C_p + n$). Terms are sequentially augmented to the model as long as they further reduce the value of C_p.

Conclusion

Recent studies have shown that simple trading strategies based on technical indicators can be profitable. The results are generated by a search over a universe of trading rule parameterizations, where the trading rules are based on a single indicator. The many expository volumes on technical analysis explain that the objective of technical analysis is not to predict the movement of prices, but rather to use technical indicators to time buy decisions at the beginning of up-trends and sell decision at the beginning of down-trends.

In this paper, a number of trend-following and oscillator indicators have been used as explanatory variables in regressions on the first difference of the index. The regression results show that the combination of the distance between the index and a simple moving average and a simple momentum indicator is the best combination for explaining the differenced index series.

These results suggest an important insight for future studies of trading rule profitability. Research in this area needs to concentrate on evaluating systems that combine trend-following indicators and oscillators into a trading rule. The results of this study provide a guide to the combinations of technical indicators that can be used to generate trading rules of this type. J

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TABLE 4: INDICATORS IN ORDER OF EXPLANATORY ABILITY

Period	Full	Period 3	Period 2	Period 1
Indicators	DSMA1_5	DSMA1_5	DSMA1_5	M5
	M5	M5	M5	DSMA1_5
	MACDH	MACDH	MACDH	MACDH
	M10	ROC10	DSMA1_10	M10
	DSMA1_100	DSMA1_100	DSMA1_100	DSMA1_100
	DSMA1_10	SROC5_10	SROC5_10	DSMA1_10
	SROC5_10	DSMA1_10	SROC12_25	SROC5_10
	SROC12_25	DSMA1_50	SROC10_20	SROC12_25
	ROC10	SROC10_20	M10	SROC10_20
	SROC10_20	SROC12_25	ROC10	ROC10
	DSMA1_50	M10	DSMA1_50	DSMA1_50
	ROC5			
R-Squared	0.663	0.6951	0.6895	0.6782