A COMBINED SIGNAL APPROACH TO TECHNICAL ANALYSIS ON THE S&P 500

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Abstract

This paper examines the effectiveness of nine technical trading rules on the S&P 500 from January 1950 to March 2008 (14,646 daily observations). The annualized returns from each trading rule are compared to a naïve buy-and-hold strategy to determine profitability. Over the 59 year period, only the moving-average cross-over (1,200) and (5,150) trading rules were able to outperform the buy-and-hold trading strategy after adjusting for transaction costs. However, excess returns were generated by employing a Combined Signal Approach (CSA) on the individual trading rules. Statistical significance was confirmed through bootstrap simulations and robustness through sub-period analysis.

Keywords: Technical Analysis; Market Efficiency; Combined Signal Approach; S&P 500.

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1. INTRODUCTION

Technical analysis and trading rules are considered to be one of the earliest forms of investment analysis with its origins dating back to the 1800s. It was one of the first forms of investment analysis mainly because stock prices and volume levels have been publicly available prior to other types of financial information. Technical analysts search the past prices of a time series for recognizable patterns that have the ability to predict future price movements. Currently, technical analysis is still being used by institutional and individual investors alike. However, the notion that historical data can be used to identify patterns that predict security movements violates the random walk hypothesis and the weak form of market efficiency. According to efficient market theorists, technical analysis should not be able to generate abnormal returns in an efficient market.

There have been a number of studies conducted on trading rules in equity markets. Alexander (1964) and Fama and Blume (1966) were two of the first to test technical trading rules in the United States. Both of these studies suggest that excess returns could not be realized by making investment decisions based on the movements of certain sizes after adjusting for transaction costs. The number of influential studies grew in the 1990s. Some of these studies include Jegadeesh and Titman (1993), Chan, Jagadeesh, and Lakonishok (1996), Lo and MacKinlay (1997), and Rouwenhorst (1998). Furthermore, several studies have recently emerged that signify the informational content of technical trading rules (Brock, LeBaron and Lakonishok (1992), Lisi and Medio (1997), Gençay (1999), Lo, Mamaysky and Wang (2000), and Lento, Gradojevic, and Wright (2007)).

Although there have been many studies conducted that test technical trading rules, very few have tested the notion that a combined signal approach to technical analysis should increase profitability. The

Combined Signal Approach (CSA) was first introduced by Lento and Gradojevic (2007) and was tested on the Dow Jones Industrial Average, Toronto Stock Exchange, and Canadian/U.S. Exchange Rate. The CSA was found to enhance the profitability of technical trading rules. The original study suggested that "testing the robustness of the combined signal approach is a priority" (Lento and Gradojevic, 2007, pg. 21). The purpose of this study is to provide a more robust test of, and further evidence on, the CSA. This study tests the CSA on a stock market that differs from the original study, the S&P 500, and for a much longer time period (14,646 daily observations). The S&P 500 is one of the most followed markets in the world, and likely, one of the most efficient. Therefore, given the data set and time period, this study provides very robust and generalizable empirical evidence on the profitability of the CSA.

The same nine technical trading rules have been employed in an attempt to exploit any recognizable trends on the S&P 500. The results demonstrate, on average, that the technical trading rules alone are unable to earn returns in excess of the buy-and-hold trading strategy after adjusting for transaction costs. Only the (1, 200 day) and (5, 150 day) moving average cross-over rules were able to earn excess returns. However, the CSA was able to improve the profitability of the trading rules by earning excess returns. The profitability of the CSA is significant to both individual and institutional investors alike – the combination of individual technical trading rules provides a synthesis whereby the whole is greater than the sum of the parts and excess profits are available. The statistical significance (p-value) was assessed through bootstrap simulations and robustness through sub-period analysis.

The remainder of the paper is organized as follows. The next section describes the trading rule strategies. Section 3 described the data. Section 4 explains the methodology. Section 5 presents the results. Conclusions and recommendations for future research in Section 6.

2. TRADING RULES

The three rules tested are moving average cross-over rules, filter rules (momentum strategies) and trading range break-out rules. Brock, Lakonishok, & LeBaron (1992) ("BLL") discuss the potential biases that can arise from identifying and testing patterns in security returns in the same dataset. As such, the same trading rules as BLL are tested, along with three common filter rules. This will help reduce the possibility of data snooping as the datasets are not searched for successful trading rules ex-post. Testing the trading rules on subsets for robustness also mitigates the effects of data mining discussed by Allen and Karjalainen (1999).

A moving average cross-over (MAC-O) rule compares a short moving average to a long moving average. The MAC-O rule tries to identify a change in a trend. There are two categories of the MAC-O rule: variable length moving average (VMA) and fixed length moving average (FMA). The FMA stresses that the returns for a few days following the crossing of the moving averages should be abnormal. The VMA generates a buy (sell) signal whenever the short average is above (below) the long average. This study tests the VMA rule based on the following buy and sell signals:

Equation 1 – VMA Buy Signal

$$\frac{\sum_{s=1}^{S} R_{i,t}}{S} > \frac{\sum_{l=1}^{L} R_{i,t-1}}{L} = Buy, \tag{1}$$

Equation 2 – VMA Sell Signal

$$\frac{\sum_{s=1}^{S} R_{i,t}}{S} < \frac{\sum_{l=1}^{L} R_{i,t-1}}{L} = Sell, \tag{2}$$

where $R_{i,t}$ is the log return given the short period of S (1 or 5 days), and $R_{i,t-1}$ is the log return over the long period L (50, 150 or 200 days). These are the same buy and sell signal used by Ratner and Leal (1999) and various other researchers. The following short, long combinations will be used to test the VMA: (1, 50), (1, 200) and (5, 150).

Filter rules generate buy and sell signals based on the following logic: Buy when the price rises by *f* per cent above the most recent trough and sell when the price falls *f* per cent below its most recent peak. The filter size (*f*) is the parameter that defines a filter rule. This study tests the filter rule based on three parameters: 1-per cent, 2-per cent, and 5-per cent.

The trading range break-out (TRB-O) rule, also referred to as resistance and support levels, generates a buy signal when the price breaks-out above the resistance level and a sell signal when the price breaks below the support level. The resistance level is defined as the local maximum, and the support level is defined as the local minimum (BLL). At the resistance (support) level, intuition would suggest that many investors are willing to sell (buy). The selling (buying) pressure will create resistance (support) against the price rising (falling) above the peak (trough) level. The TRB-O rule is examined by calculating the local maximum and minimum based on 50, 150 and 200 days as defined in Equation 3.

Equation 3 – Trading Range Break-Out Positions

$$\begin{aligned}
Pos_{t+1} &= Buy, && \text{if } P_t > \mathit{Max}\ \{P_{t-1}, P_{t-2}, \ldots, P_{t-n}\} \\
Pos_{t+1} &= Pos_t, && \text{if } P_t > \mathit{Min}\ \{P_{t-1}, P_{t-2}, \ldots, P_{t-n}\} \leq P_t \leq \mathit{Max}\ \{P_{t-1}, P_{t-2}, \ldots, P_{t-n}\} \\
Pos_{t+1} &= Sell, && \text{if } P_t < \mathit{Min}\ \{P_{t-1}, P_{t-2}, \ldots, P_{t-n}\}
\end{aligned} \qquad (3),$$

where P_t is the stock price at time t.

3. Data Description

The technical trading rules are tested on the S&P 500 for the period of January 1, 1950 to March 19, 2008. There are a total of 14,646 observations of daily stock returns. The trading rules can be calculated at various data frequencies. Investors can use high-frequency data, such as intra-day data, or longer horizons, such as weekly or yearly, when using the trading rules. The data frequency selected by a technical investor depends on many different factors and personal preferences. This research study utilizes daily closing prices. The 59 year period provides a sufficient number of daily observations to allow for the formation, recurrence and investigation of the technical trading rules. The daily returns are calculated as the holding period return of each day as follows:

Equation 4 – Daily Holding Period Return

$$r_t = \log (p_t) - \log (p_{t-1}) \tag{4}$$

where p_t denotes the market price.

4. METHODOLOGY

Profitability is determined by comparing the returns generated by the trading signals to the buy-and-hold return. The methodology relies on this relatively simple technique for analyzing the profitability of the trading rules because of the possible problems related to non-linear models such as computational expensiveness, overfitting, data snooping and difficulties interpreting the results (see White (2005) for a thorough discussion of these issues). As such, the returns are subject to sophisticated tests of significance. The returns from the buy-and-hold strategy are calculated by investing in the security at the beginning of the data set, given the trading rule parameters, and holding the security until the end of the data set. For example, no trading signal can be generated until the 50th day with a 1-day, 50-day MAC-O rule. Therefore, the buy-and-hold returns will be calculated commencing the 50th trading day.

The trading rule returns are also calculated in a relatively simple manner. The returns resulting from the MAC-O rules are based on the variable moving average signals. More precisely, when a buy signal is triggered as per Eq. 1, the investor will take a long position, and returns will be calculated at the market rate. When a sell signal is triggered as per Eq. 2, the investor is out of the market and returns will be based on a notional interest rate (3 per cent APR or 0.0089 daily EAR) because the data sets are not adjusted for inflation.

The returns resulting from the filter rule and TBR-O rule are calculated in a slightly different manner. At the beginning of the trading period, the investor will be short and earn the notional interest rate. To minimize the measurement error due to non-synchronous trading made evident by Scholes and Williams (1977) the investor will be long the market one day after the trading signal is generated. Therefore, once a buy signal is generated, the investor will be long on the following day, and returns will be calculated based on the market returns. Finally, if the investor is long (short), and a buy (sell) signal is generated, the position is carried forward.

Similar to Gencay (1998a), the returns generated from the trading rules are adjusted for transaction costs. Both the bid-ask spread and brokerage trading costs are included into the total transaction cost. The bid-ask spread for the S&P 500 exchange traded fund is used as a proxy for the actual index. The returns are adjusted downward when a trade is triggered. This adjustment factor approximates the average transaction costs for these securities.

The significance of the results is tested by using the bootstrap approach developed by Levich and Thomas (1993). This approach, first, observes the data set of closing prices, with the sample size denoted by $N+1$ that corresponds to a set of N returns. The m^{th} ($m=1,\ldots,M$) permutation of these N returns ($M=N!$) is related to a unique profit measure ($X[m, r]$) for the r^{th} trading rule variant ($r = 1,\ldots,R$) used in this study. Thus, for each variable, a new series can be generated by randomly reshuffling the returns of the original series.

From the sequence of M returns, the starting and ending points of the randomly generated time series are fixed at their original values. This maintains the distributional properties of the original data. However, the time series properties are random. In this bootstrapping simulation one can thus generate one of the various notional paths that the returns could have taken from time t (starting day) to time $t+n$ (ending day). The notional paths are generated 50 times for each data set. Technical trading rules are then applied to each of the 50 random series and the profits $X[m, r]$ are measured. This process generates an empirical distribution of the profits. The profits calculated on the original data sets are then compared to the profits from the randomly generated data sets. A simulated p-value is produced by computing the proportion of returns generated from the simulated series that is greater than the return computed with the actual series.

The null and alternative hypotheses are given by:

H_0: the trading rules provide no useful information.

H_1: the trading rules provide useful information.

Robustness testing will be performed to mitigate the effects of data mining and to further analyze the significance of the trading rule profits. To test the returns for robustness, returns will be calculated on three sub-periods of the original data. The sub-periods are determined by arbitrarily dividing the data sets into thirds and then testing for structural breaks between the subsets. The Chow Test is used to test for structural breaks. The subsets are used to test for robustness if the parameters of each subset are determined to be non-stationary. Three new subsets are selected if the parameters of the subsets are constant. The returns from each trading rule and the buy-and-hold strategy, along with the Sharpe ratio, are computed for each sub-period. Consistent excess returns and stable Sharpe ratios across the sub-periods are associated with robust returns.

5. EMPIRICAL RESULTS

5.1 PROFITABILITY OF THE TRADING RULES

The profitability of the technical trading rules is presented in Table 1, along with the resulting p-values from the bootstrapping simulations. A p-value of 0.00 occurs when the original return was the highest of any of the randomly generated returns. Note that Table 1 presents the number of trades as opposed to signals. The number of trades is more relevant because transaction costs are a function of trades, not signals. The number of signals does not represent the number of trades because if an investor is long (short) in the market, no trade is triggered if a long (short) signal is generated.

Insert TABLE 1 about here

The MAC-O rules were the most profitable as all three variants were able to outperform the buy-and-hold training strategy before adjusting for transaction costs. After adjusting for transaction costs, two of the three variants were able to earn excess returns. All of the excess returns were significant at the 5 percent level of significance.

The 1-percent filter rule was able to beat the market by 5.2%; however, the excess returns disappeared after adjusting for transaction costs. The fact that the 1-percent filter rule was able to out-perform the buy-and-hold trading strategy suggests that there are some momentum patterns in the market; contradictory to the weak form of market efficiency. However, investors are not able to exploit these returns after accounting for brokerage fees and the bid-ask spread. There is no evidence of the 2-percent or 5-percent filter rule out-performing the market.

None of the TRB-O rules were able to beat the market. The 200-day trading range break-out rule performed the best of the variants tested. The TRB-O's lack of profitability is consistent with past studies (Lento 2007).

The results of this study suggest that, on average, trading rules based on short-term momentum are better at providing statistically significant excess returns. However, overall, the results of the individual trading rules are not exceptional. The bootstrapping simulation provides some support against the weak form of market efficiency as the MAC-O rules and the 1-percent filter rule consistently generate significant excess returns. However, much of the excess returns disappear after adjusting for transaction costs. These results are consistent with Fama and Blume's original study on technical analysis from 1966 and suggest that technical trading rules are still not able to outperform the market.

Similar to Gençay (1998b), the trading rules were tested for robustness on sub-periods. Table 2 present the returns for the sub-periods, along with the Sharpe Ratio for each period.

Insert TABLE 2 about here

The sub-period analysis suggests that the returns from technical trading rules are not robust. None of the nine trading rules tested have positive returns in all three sub-periods. Furthermore, the Sharpe Ratio is not stable and frequently changes across sub-periods that exhibit consistent excess returns. The most robust returns were generated from the MAC-O rules. It is interesting to note that overall the trading rules performed the worst during the period of 1990 – 2008 as 8 of the 9 trading rules were unable to beat the buy-and-hold trading strategy. However, inconsistent return/risk ratios across sub-periods are in line with prior studies (Lento, 2007). Dooley and Shafer (1983) suggest that the inconsistent return/risk ratios across sub-periods suggest that the returns earned by the profitable technical trading rules over the entire period are risky.

5.2 SIGN PREDICTION ABILITY

Aside from determining the profitability of the trading rules, this paper also seeks to determine the sign prediction ability of the trading signals. Sign prediction ability refers to whether the predicted trading signal is correct, i.e., on the right side of the trade. The percentage of correct trading signals as well as prediction-implied daily percentage returns for 1-day and 10-day forecasting horizons are presented in Table 3.

Insert TABLE 3 about here

In total, 36 possible trading positions are investigated: 9 trading rules x 2 (buy or sell signal) x 2 (lag-1 or lag-10) x 1 data set. The results indicate that 22 of 36 (57.9 per cent) rules predict a correct signal more than 50 per cent of the time. To assess the probability of the randomness of each correct signal, the Binomial Probability Distribution can be used. Based on a 5 per cent significance level, 12 of the 36 signals provide relevant information regarding future price movements. The buy signals are correct more often than the sell signals as 9 of the 12 significant signals are buy signals and the remaining 3 are the sell signals. All of the buy signals generated by the MAC-O and TRB-O rules were significant. The sign prediction ability of the TRB-O rules on the S&P 500 is consistent with the results for the TSX (Lento and Gradojevic 2007).

An alternative approach to evaluate the predictive ability is to calculate daily returns of the forecasted trading recommendations. Table 4 summarizes the daily returns by calculating the average predicted (daily) return for each time series. The aggregation of the daily returns allows for comparisons to be made between BLL and this paper.

Insert TABLE 4 about here

The BLL's results showed that returns following buy signals are larger than returns following sell signals. The results of this paper support their conclusion as the returns in buy periods are larger than those of sell periods. Interestingly, the daily returns following buy signals are positive at the 1-day forecasting horizons. Despite this considerable support to the idea that technical trading rules can be informative, the results from the sell signals are mixed. The notion of price predictability with regard to technical trading rules remains unsettled.

5.3 A Combined Signal Approach

The returns presented so far have been calculated based on the signals generated from individual trading rules. Many researchers and technicians have argued that a single trading rule should not be used alone to make trading decisions (Murphy, 2000). One of the major concerns with utilizing only one trading rule is that there is no theory to guide an investor when making a decision amongst the many different types of trading rules. For example, there is no theoretical framework for choosing a MAC-O rule over the TRB-O rule. Furthermore, once a rule is selected, it is not clear how to choose the underlying parameters. This problem may be mitigated by jointly employing all of the trading rules based on the notion that information related to future price movements is somewhat dispersed and combining trading signals may generate a more informative signal. It is also possible that the combination of individual technical trading rules provides a synthesis whereby the whole is greater than the sum of the parts and excess profits can be generated. Also, combining the signals and using a consensus position reduces the risk of selecting and relying on a single rule at any given time.

Table 5 presents the returns generated by the CSA. While utilizing all nine trading signals, a combined signal is received using the following decision rule: a long (short) position is taken if 'x' or more of the 9 trading rules suggest a long (short) position. The CSA was tested for the following: (2 / 9), (3 / 9), (4 / 9), (5 / 9), and (6 / 9). There are not enough observations at the (7 / 9) or greater to allow for robust testing.

Insert TABLE 5 about here

Before transaction costs, all CSA variants indicate an ability to outperform the market. After accounting for transaction costs, the CSA (2 / 9), and (4 / 9) were able to beat the market, while the (3 / 9) earned the same return as the S&P 500. The CSA (5 / 9) and (6 / 9) profitability disappeared after adjusting for transaction costs. Recall Table 1. The same bootstrapping techniques used on the individual trading rules are applied to the returns generated by the combined signal. The results of the bootstrapping simulations reveal that all of the returns are significant at the 5-percent level of significance.

The CSA results are in stark contrast to the weak form of the efficient market hypothesis. Relative to the buy-and-hold strategy, individual trading rules consistently underperformed on the S&P 500. However, the CSA consistently earns excess returns on the S&P 500. Therefore, the CSA represents a significant improvement in profitability from the individual technical trading rules, and removes an investor's potential conflict during periods of conflicting trading signals.

The sub-period analysis for the CSA is presented in Table 6. After adjusting for transaction costs, the CSA (2 / 9) was able to earn excess returns in all three sub-periods with a relatively stable Sharpe Ratio.

Insert TABLE 6 about here

6. Conclusions and Discussion

An empirical study was conducted to determine if the CSA approach to technical analysis is profitable on the very efficient and robust S&P 500 data set. The profitability of nine trading rules was also tested. Profitability was defined as returns in excess of the buy-and-hold trading strategy. The results demonstrate, on average, that the CSA increases the profitability of the individual trading rules. Before adjusting for transaction costs, all of the CSA variants tested were able to beat the buy-and-hold trading strategy. Some of the profitability was eliminated after adjusting for transaction costs. However, even if an investor cannot earn a profit after adjusting for transaction costs, a Bayesian investor could alter his asset allocation in response to this information (Bessembinder and Chan 1998). Therefore, these results may have significant economic implications.

This study confirms the results obtained in the Lento and Gradojevic (2007) and Lento (2008), whereby, the CSA was profitable. The results also support the notion that a synergy is created by the CSA, and that the combining the signals creates a more powerful, and profitable trading signal. The results of this study provide robust support for the profitability of the CSA. It differs from the original CSA tests because it provides a more comprehensive test by using one of the most followed and efficient market index over a 59 year period (14,646 daily observations). Therefore, the results of this study are the most robust on the CSA to date. As such, this study contributes to the overall understanding of the efficiency and price behaviour of the S&P 500, along with the profitability of the CSA.

The results of the CSA are impressive, and indicate that further research in this area is warranted. Future researchers are encouraged to further develop the CSA. Future researchers are encouraged to learn more about what alternative weighting schemes and trading rules are likely to be more successful and in what circumstances. Moreover, it may be possible to determine the optimal number of rules for the decision-making mechanism using a more complex methodology. Developing a fully artificial intelligence-based combined signal may be a promising and challenging direction for future research.

Future research can also focus on adjusting the strength of a CSA signal based on the volume of the given index. Utilizing volume to determine the strength of a trading signal is not a new notion as it has been successfully utilized on individual trading rules.

REFERENCES

1. Allen, F. & R. Karjalainen (1999). Using Genetic Algorithms to Find Technical Trading Rules. *Journal of Financial Economics,* 51, 245-271.
2. Alexander, S. (1964). Price Movements in Speculative Markets: Trends or Random Walks, No. 2 in P. Cootnered (ed.), *The Random Character of Stock Market Prices* (MIT Press, Cambridge, MA).
3. Bessembinder, H. & K. Chan, (1998). Market efficiency and the returns to technical analysis. *Financial Management,* 27 (2), 5-17.
4. Brock, W., J. Lakonishok, & B. LeBaron (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *Journal of Finance*, 47, 1931-1764.
5. Chan, L., N. Jegadeesh, & J. Lakonishok (1996). Momentum Strategies. *Journal of Finance*, 51, 1681-1713.
6. Dooley, M. P. & J.R. Shaler (1983). Analysis of Short-Run Exchange Rate Behaviour: March 1973 to November 1981 in *Exchange Rate and Trade Instability: Causes, Consequences, and Remedies*. Cambridge, MA.
7. Fama, E. & M. Blume (1966). Filter Tests and Stock Market Trading. *Journal of Business*, Vol. 39, pp. 226-241.
8. Gençay, R. (1998b). Optimization of Technical Trading Strategies and the Profitability in Security Markets. *Economics Letters*, Vol. 59, pp. 249-254.
9. Gençay, R. (1998a). The Predictability of Security Returns with Simple Technical Trading Rules. *Journal of Empirical Finance,* 5 (1998) 347-359
10. Gençay, R. (1999). Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules. *Journal of International Economics,* 47, 91-107.
11. Jegadeesh, N. & S. Titman (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 65-91.
12. Lento, C. (2007). Test of Technical Analysis in the Asian-Pacific Equity Markets: A Bootstrap Approach. *Academy of Accounting and Financial Studies Journal* 11(2), 51 - 74.

13. Lento, C. and Gradojevic, N. (2007). The Profitability of Technical Trading Rules: A Combined Signal Approach. *Journal of Applied Business Research* 23(1), 13-27.

14. Lento, C., Gradojevic, N. and Wright, C.S. (2007). Investment Information Content in Bollinger Bands? *Applied Economics Letters* 3(4), 263 - 267.

15. Levich, R. and L. Thomas (1993). The Significance of Technical Trading Rules Profits in the Foreign Exchange Market: A Bootstrap Approach. *Journal of International Money and Finance,* 12, 451-474.

16. Lisi, F. & A. Medio (1997). Is a random walk the best exchange rate predictor? *International Journal of Forecasting,* 13, 255-267.

17. Lo, A. W., & A.C. MacKinlay (1997). Maximizing Predictability in the Stock and Bond Markets. *Macroeconomic Dynamics,* 1, 102-134.

18. Lo, A. W., H. Mamaysky, & J. Wang (2000). Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation. *The Journal of Finance* 55 (4), 1705-1765.

19. Murphy, J. (2000). *Charting Made Easy*. Marketplace Books, 2000

20. Ratner, M., & R.P.C. Leal, (1999). Tests of technical trading strategies in the emerging equity markets of Latin America and Asia. *Journal of Banking and Finance,* 23, 1887-1905.

21. Rouwenhorst, G. (1998). International Momentum Strategies. *Journal of Finance,* 53, 267–284.

22. Scholes, M., & J. Williams (1977). Estimating betas from non-synchronous data. *Journal of Financial Economics,* 5, 309 - 327.

23. White, H. (2005). Approximate Nonlinear Forecasting Methods. G. Elliot, C.W.J. Gragner, and A. Timmerman, eds., *Handbook of Economics Forecasting,* (in press).

Table 1 – Profitability of Technical Trading Rules

	MA Cross-Over Rule Short (days) / Long (days)			Filter Rule (in %)			Trading Range Break-Out (days of local max/min)		
Market Index	**1 / 50**	**1 / 200**	**5 / 150**	**1%**	**2%**	**5%**	**50**	**150**	**200**
S&P500 (N = 14,646)									
No Transaction Cost									
Annual Return	11.0%	11.3%	10.8%	15.0%	7.3%	7.9%	7.7%	8.9%	8.9%
Buy & Hold Return	9.7%	9.5%	9.7%	9.8%	9.8%	9.8%	9.7%	9.7%	9.5%
Over / (Under) Performance	**1.3%**	**1.9%**	**1.1%**	**5.2%**	(2.4%)	(1.8%)	(2.0%)	(0.7%)	(0.5%)
No. of Trades	861	341	215	3,157	1,481	187	1,244	813	750
p-value	0.02*	0.02*	0.00*	0.00*	0.34	0.28	0.32	0.14	0.12
S&P500 (N = 14,646)									
Transaction Costs									
Annual Return	7.7%	10.0%	10.0%	7.1%	0.9%	7.5%	7.0%	8.7%	8.8%
Buy & Hold Return	9.7%	9.5%	9.7%	9.8%	9.8%	9.8%	9.7%	9.7%	9.5%
Over / (Under) Performance	(2.0%)	**0.5%**	**0.3%**	(2.6%)	(8.8%)	(2.2%)	(2.7%)	(0.9%)	(0.7%)
No. of Trades	861	341	215	3,157	1,481	187	1,244	813	750
p-value	0.02*	0.02*	0.00*	0.00*	0.98	0.28	0.32	0.16	0.14

* Significant p-values at the 5% level.

Table 2 – Profitability of Technical Trading Rules on Sub-Periods

	S&P 500 No Transaction Costs						S&P 500 Transaction Costs					
	01/01/1950 - 31/12/1969		01/01/1970 - 31/12/1989		01/01/1990 - 19/03/2008		01/01/1950 - 31/12/1969		01/01/1970 - 31/12/1989		01/01/1990 - 19/03/2008	
	Excess Return	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**
Trading Rule												
MA (1, 50)	2.9%	0.0811	4.2%	0.0484	(3.2%)	0.0299	0.0%	0.0662	0.9%	0.0370	(7.0%)	0.0072
MA (1, 200)	2.3%	0.0694	3.5%	0.0466	(0.3%)	0.0306	1.4%	0.0650	2.1%	0.0412	(2.0%)	0.0246
MA (1, 150)	1.4%	0.0669	2.5%	0.0429	(0.4%)	0.0312	0.7%	0.0636	1.6%	0.0393	(1.3%)	0.0279
Filter Rule (1%)	4.7%	0.0879	14.5	0.0848	(3.8%)	0.0192	(1.3%)	0,0583	5.6%	0.0537	(12.3)	-0.0148
Filter Rule (2%)	(0.6%)	0.0617	0.9%	0.0285	(5.9%)	0.0111	(6.6%)	0.0300	(10.4%)	-0.0093	(9.2%)	-0.0020
Filter Rule (5%)	(2.6%)	0.0551	1.1%	0.0340	(4.0%)	0.0169	(2.7%)	0.0542	0.5%	0.0321	(4.5%)	0.0154
TRB-O (50 days)	(2.8%)	0.0488	(1.2%)	0.0280	6.4%	0.0574	(3.5%)	0.0453	(2.0%)	0.0251	(2.5%)	0.0246
TRB-O (150 days)	(2.4%)	0.0454	0.4%	0.0292	0.0%	0.0303	(2.7%)	0.0444	(0.2%)	0.0286	(0.2%)	0.0298
TRB-O (200 days)	(3.4%)	0.0390	(0.9%)	0.0258	3.0%	0.0387	(3.6%)	0.0380	(1.0%)	0.0252	2.9%	0.0385
	Chow Test (p-value) for structural break between all three sub-periods: 0.000						Chow Test (p-value) for structural break between all three sub-period 2 & 3: 0.000					

Table 3 - Percentage of correctly predicted trading signals and daily returns

Market	MA Cross-Over Rule Short (days) / Long (days)			Filter Rule *f* [%]			Trading Range Break-Out (days of local max/min)		
	1/50	**1/200**	**5/150**	**1%**	**2%**	**5%**	**50**	**150**	**200**
S&P500 (N = 14,646)									
Buy Signal									
Correct Indicator % (Lag 1/10)	**60.0** / **62.1**	50.0 / **65.3**	54.2 / **68.2**	45.8 / 55.4	50.0 / 56.4	57.6 / 57.6	59.3 / **65.9**	**60.8** / **63.2**	**61.5** / **63.4**
Daily Ave. % Return after Signal (Lag 1/ 10)	0.19 / 0.51	0.09 / 0.67	0.12 / 0.69	(0.14) / 0.12	(0.04) / 0.39	0.14 / 0.70	0.10 / 0.27	0.07 / 0.24	0.07 / 0.24
Sell Signal									
Correct Indicator % (Lag 1/10)	50.1 / 45.2	47.4 / 38.6	50.9 / 47.2	40.8 / 41.5	41.7 / 41.2	**60.0** / 39.8	55.2 / 46.5	59.9 / **80.0**	**60.0** / 44.4
Daily % Return after Signal (Lag 1/10)	(0.06) / 0.02	0.07 / 0.43	(0.24) / (0.17)	0.18 / 0.35	0.20 / 0.38	(0.05) / 0.48	(0.10) / 0.29	(0.16) / 0.20	(0.13) / 0.35

Table 4 - Average daily return following a trading signal

Market	Average daily return after trading signal	
	Lag 1	**Lag 10**
S&P500 (N = 14,646)		
Buy Signals	0.07%	0.43%
Sell Signals	-0.03%	0.26%

Table 5 – Profitability of the Combined Signal Approach (CSA)

	CSA				
	2/9	**3/9**	**4/9**	**5/9**	**6/9**
S&P500 (N = 14,646)					
No Transaction Costs					
Annual Return	12.7%	11.2%	11.3%	11.2%	9.5%
Buy-and-Hold Return	9.5%	9.5%	9.5%	9.5%	9.5%
Over/(Under) Performance	3.2%	1.8%	1.9%	1.8%	0.0%
Number of trades	405	451	445	493	691
p-value	0.00*	0.01*	0.00*	0.00*	0.04*
S&P500 (N = 14,646)					
Transaction Costs					
Annual Return	11.1%	9.5%	9.6%	9.3%	6.8%
Buy-and-Hold Return	9.5%	9.5%	9.5%	9.5%	9.5%
Over/(Under) Performance	1.6%	0.0%	0.1%	(0.2%)	(2.6%)
Number of trades	405	451	445	493	691
p-value	0.00*	0.02*	0.00*	0.00*	0.05*

Table 6 – Profitability of CSA on Sub-Periods

	S&P 500 No Transaction Costs						S&P 500 Transaction Costs					
	01/01/1950 - 31/12/1969		01/01/1970 - 31/12/1989		01/01/1990 - 19/03/2008		01/01/1950 - 31/12/1969		01/01/1970 - 31/12/1989		01/01/1990 - 19/03/2008	
	Excess Return	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**	**Excess Return**	**Sharpe Ratio**
CSA (2,9)	2.1%	0.0614	5.1%	0.0443	2.5%	0.0354	0.8%	0.0558	3.2%	0.0384	0.8%	0.0304
CSA (3,9)	1.5%	0.0626	4.5%	0.0466	(0.9%)	0.0271	0.2%	0.0567	2.5%	0.0394	(2.8%)	0.0205
CSA (4,9)	2.7%	0.0711	4.3%	0.0489	(1.5%)	0.0267	1.4%	0.0651	2.4%	0.0418	(3.5%)	0.0193
CSA (5,9)	0.9%	0.0672	4.3%	0.0533	0.0%	0.0344	(0.8%)	0.0582	2.4%	0.0453	(2.14%)	0.0262
CSA (6,9)	(0.7%)	0.0651	2.5%	0.0500	(1.9%)	0.0315	(3.0%)	0.0520	0.0%	0.0386	(5.13%)	0.0168
	Chow Test (p-value) for structural break between Sub-period 1 & 2: 0.000						Chow Test (p-value) for structural break between Sub-period 1 & 2: 0.000					
	Chow Test (p-value) for structural break between Sub-period 2 & 3: 0.000						Chow Test (p-value) for structural break between Sub-period 2 & 3: 0.000					