THE UNIVERSITY *of York*

Discussion Papers in Economics

No. 12/11

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Andrew Clare, James Seaton, Peter N. Smith and Stephen Thomas

Department of Economics and Related Studies
University of York
Heslington
York, YO10 5DD

BREAKING INTO THE BLACKBOX: Trend Following, Stop Losses, and the Frequency of Trading: the case of the S&P500

Andrew Clare*, James Seaton*, Peter N. Smith‡ and Stephen Thomas*

*Cass Business School, London, ‡University of York, UK

This Version: 10th March, 2012

Abstract

In this paper we compare a variety of technical trading rules in the context of investing in the S&P500 index. These rules are increasingly popular both among retail investors and CTAs and similar investment funds. We find that a range of fairly simple rules, including the popular 200-day moving average trading rule, dominate the long only, passive investment in the index. In particular, using the latter rule we find that popular stop loss rules do not add value and that monthly end of month investment decision rules are superior to those which trade more frequently: this adds to the growing view that trading can damage your wealth. Finally we compare the MA rule with a variety of simple fundamental metrics and find the latter far inferior to the technical rules over the last 60 years of investing.

Key words: trend following, S&P500, stop losses, trading frequency, fundamental investment metrics.

1.Introduction

Trend following is a popular investment technique among CTAs and quantitative, systematic investors more generally. The most common approach is based on moving averages where the current market price of an asset is compared with an average of historical prices of the same asset over some window, often 200 or so trading days (approximately 10 months): if the current price is above (below) the moving average, (or indeed perhaps the moving average plus or minus a few percentage points around it to avoid 'whipsaw' trading), the rule gives a buy (sell) signal. In this paper we investigate a variety of trend following models using the S&P500 with particular reference to a number of practical features which are of particular interest to fund managers and their clients:

i) is there any advantage in more complex trend following methods or are simpler trend following rules as good or even superior? To this end we compare a variety of moving average, crossover, channel and breakout rules.

ii) is there any advantage in trading frequently, e.g. daily, versus, say monthly. In other words, do the patterns of daily returns have sufficient mean reversion to render daily trading 'too frequent'? Momentum studies typically form portfolios based on previous (often, multi) month performance, and involve holding periods that can last for many months, or even years, whereas trend following rules are often explored using much higher frequency data.

iii) related to (ii) above, do trend following techniques lead to excessive 'whipsawing' in and out of markets, eating up transactions costs and leading to underperformance?

iv) related closely to (ii) and (iii) above, is there any point in applying 'stop-loss' rules? These rules, which seek to liquidate positions once a certain drawdown or calendar time loss has been experienced, are widely used in the fund management industry and much loved by practitioners and clients alike (see for example Kaminski and Lo (2008)); yet as Kaminski and Lo point out, there is little evidence regarding the usefulness of such techniques.

v) finally, is there evidence to suggest that fundamental valuation metrics offer superior decision rules for equity investing versus simple trend following rules? The wide range of practical valuation metrics include dividend and earnings yields, together with the relative yields on bonds and equities.

2. Trend Following and Momentum Strategies

A momentum strategy is a simple trading rule which involves taking a long investment position in rank-ordered, relatively good performing assets (winners) and a short position in those which perform relatively poorly (losers) over the same investment horizon. It is an explicit bet on the continuation of past relative performance into the future. There exists a large body of empirical support for the generation of abnormal momentum-based returns in a variety of contexts. Both Jegadish and Titman (2001) and Conrad and Kaul (1998) find evidence of momentum effects in US stocks; while Rouwenhorst (1998) find similar evidence for European stocks. More recently researchers have found similar momentum-based investment opportunities across equity index, currency, commodity and bond futures (see for example Asness, Moskowitz and Pedersen (2009), and Moskowitz, Ooi and Pedersen (2010). However, both Korajczyk and Sadka (2004) and Lesmond, Schill and Zhou (2004) suggest that once transactions' costs are fully incorporated into these momentum-based trading rules, especially the cost of short-selling, then the abnormal profits that appear to be available to the equity strategies disappear, though the finding that abnormal profits persist for commodity futures where transactions' costs are much lower suggest that momentum profits may be more pervasive elsewhere (see for example Szakmary, Shen, Sharma (2010) and Miffre and Ralis (2007)).

Trend following, although closely related to momentum investing, is fundamentally different in that it does not order the past performance of the assets of interest, though it does rely on a continuation of, or persistence in price behaviour based upon technical analysis. There is a tendency at times to use the terms 'momentum' and 'trend following' almost interchangeably, yet the former has a clear cross sectional element to it in that the formation of relative performance rankings is across the universe of stocks (or other securities) over a specific period of time, only to be continued in a time-series sense and eventually mean reverting after a successful 'winning' holding period. It should also be noted that momentum studies usually use monthly data whereas trend following rules are applied to all frequencies of data.

The underlying economic justification for trend following rules lies in behavioural finance tenets such as those relating to herding, disposition, confirmation effects, and representativeness biases (for example see Hurst, Ooi and Pedersen (2010) or Ilmanen (2011)). At times information travels slowly, especially if assets are illiquid and/or if there is high information uncertainty; this leads to investor underreaction. If investors are reluctant to realise small losses then momentum is enhanced via the disposition effect. Indeed both of these phenomena relate to the difference between the current price and the purchase price: poorly anchored prices allow more leeway for sentiment-driven changes. And there is now growing academic evidence to suggest that these trend following strategies can produce attractive, risk-adjusted returns (Szakmary *et al*, and references therein), though Park and Irwin (2005a, 2005b) in reviewing 9 studies using trading rules for commodity futures report mixed findings. Ilmanen (2011) suggests that the typical Sharpe ratio for a single asset using a trend following strategy lies between 0 and 0.5 but rises to between 0.5 and 1 when looking at a portfolio.

In summary then, although many studies examine exhaustively a variety of trading rules, especially of late those applied to commodity futures (see Szakmary *et al* (2010)), there is no consideration of the very practical questions relevant to fund managers and clients alike, namely how frequent should investment decision-making be? And how useful are stop losses? And, indeed, how do simple MA rules fare in comparison with fundamental valuation metrics. Here we find the rather surprising conclusions, albeit only for the case of the S&P500, that:

i) there is no advantage in trading daily rather than monthly;

ii) there is no value in stop loss rules;

iii) 'whipsawing' is not a problem provided the technical signals are of reasonable length(not too short)

iv) there is no advantage in complicated trend following rules versus simple rules;

iv) trend following rules give superior risk-adjusted returns relative to using fundamental financial metrics

3. Trend Following Rules and the S&P500

We consider 3 types of trend following rules that are all popular with investors:

1) simple daily moving averages, where the buy signal occurs when the S&P 500's index value moves above the average; we consider moving averages ranging from 10 to 450 days;

2) moving average crossovers where the buy signal occurs when the shorter duration average of the S&P 500's index value moves above the longer duration average, and which ranged from 25/50 days through 150/350 days; and

3) breakout rules, which indicate a buy signal when the S&P 500's index value trades at a 'x-day' high, where 'x' ranges from 10 to 450 days.

The intuition behind the simple trend following approach is that while current market price is most certainly the most relevant data point it is less certain whether the most appropriate comparison is the price a week ago or a month or a year ago, (Ilmanen (2011)). Taking a moving average therefore dilutes the significance of any particular observation. With each of the rules, if the rule 'says' invest we earn the return on the S&P 500 index over the relevant holding period, however when the return 'says' do not invest we earn the return on cash over the holding period relevant period. The rules are therefore binary: we either earn the return on the risky asset – US equities, as represented by the S&P500 index; or the return on cash.

The moving average crossover technique also smoothes the current observation with a shorter length moving average, while acceleration or breakout signals emphasise even more the distinction between a recent/current price move and recent past: sharp moves lead to stronger signals. We utilise daily S&P 500 price and total return data from July 1988 to June 2011 and daily price and monthly return data from January 1952 to June 2011 in this study. This gives an adequate time frame over which we can evaluate the various rules.

Table 1 presents our results for the 3 classes of moving average rules based on daily signals and trading, while Table 2 uses end-of-month rules and trading. We present the passive holding of the S&P500 for comparison. Comparing daily with end-of-month decision rules we see that generally monthly rules outperform daily rules. The simple daily version of the MA rule, (with a 20 basis points transaction cost assumed for each buy and each sell) shown in Panel B of Table 1, shows that the 400 day version of the rule produces the highest Sharpe ratio of 0.54 with a return of 10.5% pa, compared with a holding period return of 9.49% and Sharpe ratio of 0.31 for the buy and hold, passive alternative. The best monthly MA rule is the 200 day rule with a return of 10.66% and a Sharpe ratio of 0.58. This elevated return with much lower volatility (often a half to a third of a buy and hold equivalent) is a typical finding for a range of asset classes and historical periods (see Faber (2007) and ap Gwilym, Clare, Seaton and Thomas (2010)). The tables show clearly that short-term signals give far worse returns than the longer signals, basically because overtrading detracts from performance. These results confirm those summarised by Ilmanen (2011) who report significant excess returns for performance based on moving averages of 6 to 12 months. An additional filter in the form of MA crossover or breakout rules may be required.

The results of applying the MA crossover rule on a daily basis are shown in Panel C of Table 1. The best returns and Sharpe values are very similar to those presented in Panel B, the Sharpe ratios are always higher than that achieved from the buy-and hold strategy and where the highest returns (10.88%) and Sharpe values (0.56) were achieved when we applied a 150/300 day crossover rule, though there is little to choose between the strategies once we extend the length of decision rule beyond 50/200. If we compare these with monthly trading for the crossover strategy in Panel B, Table 2, we see that the 100/250 crossover (monthly trading) is probably best of all, though again for lengths beyond 50//200 there is little to choose between the rules. Finally, the results of the daily calibrated breakout rule are shown in Panel D of Table 1. Here the Sharpe ratios are nearly always higher than the buy and hold equivalent once the breakout period is beyond 50 days; the 200 and 250 day breakout rules yield the highest (10.61% and 11.19%) and best quality returns (0.56 and 0.59 Sharpe ratios). For comparison the end-of-month monthly trading of breakout rules slightly dominates daily trading with breakout lengths of 200 and 250 days giving returns of 11.38% and 11.59%, with Sharpe ratios of 0.61 and 0.62, respectively.

In summary we can say, firstly, that for most cases both the daily and end-of-month trend following rules outperform the buy and hold alternative by a considerable margin with substantially reduced volatility except for very short-term technical rules. Second, in each case – moving average, moving average crossover and breakout – the best Sharpe ratios are generally higher for end-of-month investing rules than for those achieved by applying the rules on a daily basis. For example, the Sharpe ratio for the moving average rule using daily decision rules ranges from -0.79 to 0.54; the equivalent range for monthly decision making, is 0.06 to 0.59. Generally speaking, the monthly application of the rules produced higher average returns with lower return volatility.

Monthly Trading with the 200 day MA

The results from Tables 1 and 2 suggest that a simple 200 day MA rule applied at the end of the month is as successful a trading rule as any other by both the average return and the Sharpe criteria and certainly vindicates the practitioners' enthusiasm for that simple parameterisation; so what if we now compare, over a longer period of data, a monthly (end-of-month) decision rule (MA) using an average based on averaging daily prices versus end-of-month prices. For example, a 250 day MA covers a similar calendar period to 12 end-of-month prices averaged daily. The results in Table 3 include the S&P500 return and volatility for a longer time-period (1952-2011). Interestingly the best end-of-month strategy (12 months) is at least as good as the daily strategy at a return of over 11.00% and a Sharpe of 0.58, the latter being around 50% better than the passive performance. In other words there is no benefit in calculating an average based on daily data: the end-of-month suffices. The results presented in Tables 1 to 3, although covering different estimation periods, suggest that looking at the data only at the end of month may well be advantageous. Annaert, van Osslaer and Verstraete (2009) confirm this result. They show, in a portfolio insurance setting, that a stop-loss strategy generates higher returns with less frequent rebalancing but at higher risk. But what about intra-month variation? Would stop losses improve performance? If an investor only trades on a monthly basis they could incur large losses within the month. This possibility suggests that there may be a role for stop-loss rules to improve the performance of a monthly-based trading rule.

4. Do Stop Losses Work?

Stop loss rules are usually applied in the hope of reducing a portfolio's exposure to market risks after some pre-determined cumulative loss is reached, possibly with respect to daily or monthly holding periods, or simply on drawdown losses. They are rules designed to facilitate an exit from an investment after some threshold of loss has been reached, but also for re-entering an investment once some level of gain has been achieved. Both retail and institutional investors often see these rules as a way of 'protecting' their portfolios, yet as Kaminski and Lo (2008) observe, there has been very little formal analysis of such procedures possibly because the Random Walk hypothesis was the dominant paradigm in the 1960s and 1970s and since this was synonymous with market efficiency and rationality then there was little motivation to test them[1]. Gollier (1997) and Dybvig (1988) also show that stop-loss strategies are inefficient relative to other dominating strategies. A justification for such rules can be gleaned from behavioural finance with reference to the disposition effect, and loss and ambiguity aversion.

We can measure the success or otherwise of stop-loss rules by assessing their impact on portfolio expected returns. Kaminski and Lo (2008) show that if the portfolio return follows a random walk then simple stop-loss rules will always reduce a strategy's expected return whereas if the returns have momentum then such rules can indeed add value. Similarly if the returns' process is mean reverting then stop-losses may not work since the investor is stopped out after a fall only to be left stranded as the portfolio recovers. They apply such rules to a buy and hold strategy for US equities since 1950 and find that they add 50-100 bp per month during stop out periods. It is clear, and indeed intuitively appealing, that the premium from applying a stop-loss rule is closely related to the stochastic process underlying the portfolio's return and in fact is directly proportional to the magnitude of return persistence. Of course this says little about portfolio risk so it is important to also compare portfolio variance with and without stop-loss rules; unsurprisingly switching to a lower variance asset such as cash or government bonds when the stop-loss is reached leads to a lower unconditional variance of the portfolio return than otherwise would have been achieved.

Lei and Li (2009) investigate the impact of both fixed and trailing stop-loss strategies on the return and risk of individual US stocks from 1970. Using historical return paths and random starting dates for a given holding period. They show that stop-loss strategies can reduce

[1] Note that the 'filter rules' of Alexander (1961) and Fama and Blume (1966) were of a similar purpose but did not yield superior returns.

investors' effective holding periods on losing investments. In particular they are effective for stocks with high past volatility. Dybvig (1988) finds that stop-loss rules can induce large inefficiencies, though Lei and Li (2009) find no identifiable efficiency loss on either realised returns or investment risk. They provide investors with discipline and the potential to reduce investment risk and hence at least partially explain the popularity of such rules among investors. On the other hand trailing stop-loss strategies show the effect of reducing investment risk rather than reducing investment losses. Whereas most investors may see stop-loss strategies as boosting investment returns, the reality is that the value may well come largely from risk reduction.

Stop losses and trend following for the S&P500

We explore the empirical validity of various stop loss rules for the S&P500 index based on daily returns from July 1988 to June 2011. Table 4 shows two types of strategy: the first shown in Panel A involves a conventional break out and re-entry stop loss rule where the exit signal breaking through a MA on the downside (and hence selling the asset for cash) and buying again on a break to the upside. Typically the stop loss rule on the downside is a shorter signal. Interestingly the longer signals reveal higher returns and Sharpe ratios.

A popular alternative stop-loss signal involves the use of trailing stop losses. Panel B in Table 4 shows the effect of assuming a 200-day MA as a breakout as an entry signal and then stopping out using a range of falls from that entry between 3% and 15%. Clearly both the returns and volatility rise with the stop loss through to a peak return at a stop-loss of 12%. In both cases stop-loss rules would seem to make performance worse. The same is true for 'purchase cost' stop losses shown in Table 5, though they perform better than the previous two rules. This latter rule sells the S&P 500 index when the return falls below 5 standard deviations below the initial purchase price. This is the most active of the stop-loss rules considered by Lei and Li (2009). The results in Table 5 show that the rule has no beneficial impact on the returns from the MA trend-following rule. For the other two cases, returns and volatility of returns are lower. The Sharpe ratio is the same or lower in nearly all cases. These results echo those of Lei and Li (2009) in being negative for the efficacy of stop-loss rules but may be particular to the use of the traditional stop-loss rule. However, simple trend-following rules are still better than introducing stop-losses: *a change of trend is the best stop loss*.

5. Fundamental metrics versus the 10-monthTrend Following MA

How well does a popular trend-following[2] method fare as an investment decision rule against more conventional, 'fundamental 'metrics? Do trend following rules outperform signals based on fundamental metrics such as dividend and earnings' yields (Campbell and Shiller (1988)) the Fed Model (ap Gwilym, Seaton, Suddason and Thomas 2006), the relative yield on bonds and equities (Clare, Thomas and Wickens (1994), and Shiller's cyclically-adjusted price-earnings ratio(CAPE)? We test this by applying the recursive forecast method used by ap Gwilym et al (2006) effectively running a race between the alternative models. Data from 1952 onwards (from Professor Robert Shiller's website[3]) is used to estimate a future one-year nominal return for each fundamental metric as the explanatory variable at the end of each month. This forecast is then compared with the T-Bill rate. If the expected return on stocks is higher a long position is taken in this asset class, otherwise a cash position is adopted. These are then compared with the 10-month, end-of-month, MA rule as discussed earlier in this paper.

ap Gwilym et al (2006), using data from 1988 for 6 international equity markets, find that absolute valuation metrics such as earnings and dividend yield can explain a considerable amount of the variation in 5-year returns though the Fed model and other relative yield models are better at forecasting 1-year returns. Table 6 shows the results using the long period of data from January 1952 to June 2011. The table clearly shows the superiority of the end of-month 10 month rule in terms of Sharpe ratio both relative to long only S&P and the various valuation metrics; perhaps a surprising feature is the similarity of return for buy-and-hold and all prediction methods except GEYR (relative market dividend to government bond yield). The main difference yet again is the subdued volatility in the Trend Following returns leading to the highest Sharpe by some margin. Following on from results suggested, for example, by Faber (2007) and ap Gwilym et al (2010), trend following techniques will for many assets reduce volatility by a third to a half relative to long-only without sacrificing returns: Table 6 reinforces this conclusion.

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[2] Lo, Mamaysky and Wang (2000) provide evidence that algorithms implementing other popular patterns of technical analysis can provide incremental information for returns. Here we concentrate on strategies which can be given a precise analytic form.

[3] From Shiller's website *www.econ.yale.edu/~shiller/data.htm*

6. Conclusion

We have investigated the performance of various popular trend-following rules using the S&P500 as an example. Supporting the findings of, for example, Ilmanen (2011), the use of various technical rules beyond the very shortest time period (say, 50-100 days) gives superior performance compared to long only investing, emphasising that in the active versus passive investment debate there is a third way, namely the class of techniques known as trend following applied to otherwise passive indices: perhaps we should call this ‘clever passive’?

We find that it is not necessary to consider such rules on a daily basis or to impose stop-loss rules-a change of trend is simply the best stop-loss rule. Finally simple financial economic models perform far worse in risk-adjusted terms than a simple 10-month average over the last 60 year period for the S&P500: it is no surprise that such rules are popular with professional and retail investors alike.

References

Alexander, S., (1961). "Price Movements in Speculative Markets: Trends or Random Walks", *Industrial Management Review*, 2, 7-26.

Annaert, J., Van Osselaer, S., Verstraete, B., (2009). "Performance Evaluation of Portfolio Insurance Using Stochastic Dominance Criteria", *Journal of Banking and Finance*, 33, 272-280.

ap Gwilym O., Seaton, J., Suddason, K., Thomas, S., (2006). "International Evidence on the Payout Ratio, Earnings, Dividends, and Returns ", *Financial Analysts Journal*, 62, 36-53.

ap Gwilym O., Clare, A., Seaton, J., Thomas, S., (2010). "Price and Momentum as Robust Tactical Approaches to Global Equity Investing", *Journal of Investing*, 19, 80-92.

Asness, C., Moskowitz, T., and Pedersen, L., (2010). "Value and Momentum Everywhere", University of Chicago and AQR Capital Management working paper.

Campbell, J., Shiller, R., (1998). "Valuation Ratios and the Long-Run Stock Market Outlook", *Journal of Portfolio Management*, 24, 11-26.

Clare, A., Thomas, S., and Wickens, M., (1994). "Is the Gilt- Equity Yield Ratio Useful for Predicting UK Stock Returns?", *Economic Journal*, 104, 303-15.

Conrad, J., Kaul, G., (1998). “An Anatomy of Trading Strategies,” *Review of Financial Studies*, 11, 489-519.

Dybvig, P., (1988). "Inefficient Dynamic Portfolio Strategies, or How to Throw Away a Million Dollars in the Stock Market," *Review of Financial Studies*, 1, 67-88.

Faber, M., (2007). “A Quantitative Approach to Tactical Asset Allocation”, *Journal of Investing*, 16, 69-79.

Fama, E., Blume, M., (1966). "Filter Tests and Stock Market Trading" *Journal of Business*,

39, 226-241.

Gollier, C., (1997). "On the Inefficiency of Bang-Bang and Stop-Loss Portfolio Strategies", *Journal of Risk and Uncertainty*, 14, 143-154.

Hurst, B., Ooi, Y.H., Pedersen L., (2010). "Understanding Managed Futures", AQR Working Paper.

Ilmanen A., (2011). *Expected Returns*. John Wiley & Sons.

Jegadeesh, N., Titman, S., (2001). “Profitability of Momentum Strategies: An Evaluation of Alternative Explanations,” *Journal of Finance*, 54, pp. 699-720.

Kaminski, K., Lo, A., (2008). "When Do Stop-Loss Rules Stop Losses?," SIFR Research Report Series 63, Institute for Financial Research.

Korajczyk, R., Sadka, R., (2004). "Are Momentum Profits Robust to Trading Costs?," *Journal of Finance,* 59, 1039-1082.

Lei, A. Y., Li, H., (2009). "The Value of Stop Loss Strategies", *Financial Services Review*, 18, 23-51.

Lesmond D., Schill, M., Zhou C., (2004). "The Illusory Nature of Momentum Profits", *Journal of Financial Economics*, 71, 349-380.

Lo, A., Mamaysky, H., Wang, J., (2000). "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation," *Journal of Finance*, 55, 1705-1770.

Miffre, J., Rallis, G., (2007), "Momentum Strategies in Commodity Futures Markets", *Journal of Banking & Finance*, 31, 1863-1886.

Moskowitz, T., Ooi, Y.H., and Pedersen, L., (2010). "Time Series Momentum", University of Chicago Working Paper.

Park, C.H., Irwin, S., (2005a). "The Profitability of Technical Trading Rules in US Futures Markets: A Data Snooping Free Test,", University of Illinois at Urbana-Champaign Working Paper.

Park, C.H., Irwin, S., (2005b). "A Reality Check on Technical Trading Rule Profits in US Futures Markets", Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, Missouri.

Rouwenhorst, K., (1998). “International Momentum Strategies,” *Journal of Finance*, 53, 267-284.

Szakmary, A., Shen, Q., & Sharma, S., (2010). "Trend-Following Trading Strategies in Commodity Futures: A Re-Examination", *Journal of Banking and Finance*, 34, 409-426.

Table 1

Daily Trend Following Methods in the S&P 500 - July 1988 to June 2011

A. Buy-and-Hold											
Annualized Return(%)	9.49										
Annualized Volatility(%)	18.16										
Sharpe Ratio	0.31										
B. Moving Average (0.2% Transactions Cost)											
Moving Average Length (days)	10	25	50	100	150	200	250	300	350	400	450
Annualized Return(%)	-5.37	-0.21	2.53	4.32	6.48	7.68	8.63	9.50	10.05	10.50	9.50
Annualized Volatility(%)	11.54	11.17	10.88	11.11	11.34	11.52	11.72	12.06	12.16	12.33	12.35
Sharpe Ratio	-0.79	-0.36	-0.12	0.05	0.24	0.34	0.41	0.47	0.51	0.54	0.46
C. Moving Average Crossover (0.2% Transactions Cost)											
M.A. Crossover Length (days/days)	25/50	25/100	50/100	50/150	50/200	100/250	100/300	100/350	100/400	150/300	150/350
Annualized Return(%)	4.26	6.41	8.49	9.28	10.62	10.50	10.83	10.83	10.30	10.88	10.30
Annualized Volatility(%)	11.57	11.74	12.20	12.33	12.28	12.58	12.66	12.67	12.72	12.62	12.64
Sharpe Ratio	0.04	0.22	0.38	0.44	0.56	0.53	0.56	0.55	0.51	0.56	0.51
D. Breakout (0.2% Transactions Cost)											
Breakout Length (days)	10	25	50	100	150	200	250	300	350	400	450
Annualized Return(%)	-0.53	3.95	5.90	8.44	9.27	10.61	11.19	10.54	9.52	9.58	9.18
Annualized Volatility(%)	11.37	10.69	10.97	11.43	12.00	12.20	12.53	12.55	12.52	12.93	12.47
Sharpe Ratio	-0.38	0.01	0.19	0.41	0.46	0.56	0.59	0.54	0.46	0.45	0.43

Table 2

Trend Following Methods in the S&P 500 with only End-of-Month Trading - July 1988 to June 2011

A. Buy-and-Hold											
Annualized Return(%)	9.49										
Annualized Volatility(%)	18.16										
Sharpe Ratio	0.31										
B. Moving Average (0.2% Transactions Cost)											
Moving Average Length (days)	25	50	100	150	200	250	300	350	400	450	
Annualized Return(%)	4.58	6.19	7.06	8.48	10.66	10.72	9.98	10.68	10.74	11.19	
Annualized Volatility(%)	11.97	11.93	11.57	11.80	11.89	12.24	12.30	12.43	12.40	12.53	
Sharpe Ratio	0.06	0.20	0.28	0.40	0.58	0.57	0.50	0.55	0.56	0.59	
C. Moving Average Crossover (0.2% Transactions Cost)											
M.A. Crossover Length (days/days)	25/50	25/100	50/100	50/150	50/200	100/250	100/300	100/350	100/400	150/300	150/350
Annualized Return(%)	7.69	6.84	8.03	8.74	10.45	11.13	10.56	10.89	10.37	10.89	9.92
Annualized Volatility(%)	12.03	12.17	12.22	12.34	12.32	12.73	12.74	12.74	12.82	12.58	12.75
Sharpe Ratio	0.32	0.25	0.35	0.40	0.54	0.58	0.53	0.56	0.51	0.56	0.48
D. Breakout (0.2% Transactions Cost)											
Breakout Length (days)	25	50	100	150	200	250	300	350	400	450	
Annualized Return(%)	5.50	7.43	8.00	10.60	11.38	11.59	10.51	9.37	9.54	9.48	
Annualized Volatility(%)	11.80	11.43	11.80	12.25	12.34	12.55	12.58	12.60	12.98	12.51	
Sharpe Ratio	0.14	0.32	0.36	0.56	0.61	0.62	0.53	0.44	0.44	0.45	

Table 3										
End-of-Month Trend Following Methods in the S&P 500 - January 1952 to June 2011										
A. Buy-and-Hold										
Annualized Return(%)	10.54									
Annualized Volatility(%)	14.65									
Sharpe Ratio	0.39									
B. Moving Average Calculated Daily (0.2% Transactions Cost)										
Moving Average Length (days)	25	50	100	150	200	250	300	350	400	450
Annualized Return(%)	6.79	7.08	8.21	9.79	10.82	10.90	10.49	10.81	10.37	9.77
Annualized Volatility(%)	10.34	9.97	10.51	10.56	10.64	10.85	10.92	11.13	11.21	11.28
Sharpe Ratio	0.20	0.23	0.33	0.47	0.57	0.56	0.52	0.54	0.50	0.44
C. Moving Average Calculated Monthly (0.2% Transactions Cost)										
Moving Average Length (months)	4	6	8	10	12	14	16	18	20	
Annualized Return(%)	6.95	9.28	10.14	10.50	11.01	10.62	10.98	10.77	10.56	
Annualized Volatility(%)	10.82	10.53	10.60	10.57	10.84	10.95	11.06	11.11	11.20	
Sharpe Ratio	0.20	0.43	0.51	0.54	0.58	0.53	0.56	0.54	0.52	

Table 4

Using Stop-Losses with Daily Trend Following Methods in the S&P 500 - July 1988 to June 2011

A. Breakout Stop-Loss (0.2% Transactions Cost)

Opening/Closing Breakouts	50/10	50/25	100/10	100/25	100/50	150/25	150/50	200/50	200/100	250/100	250/150	250/200
Annualized Return(%)	2.48	1.24	2.17	3.12	5.83	2.58	5.28	5.15	7.48	6.92	8.29	10.04
Annualized Volatility(%)	6.86	9.16	6.13	8.24	9.88	8.09	9.77	9.53	11.04	10.91	11.65	12.08
Sharpe Ratio	-0.19	-0.28	-0.27	-0.08	0.21	-0.15	0.15	0.14	0.33	0.29	0.39	0.52

B. Percentage Stop-Loss on 200-day Breakout Strategy (0.2% Transactions Cost)

Stop-Loss Percentage (%)	3	5	7	10	12	15
Annualized Return(%)	3.02	4.47	6.82	9.52	10.13	9.61
Annualized Volatility(%)	6.83	8.71	9.77	11.08	11.70	11.91
Sharpe Ratio	-0.11	0.08	0.31	0.52	0.54	0.49

Table 5

Daily Trend Following Methods with Purchase Cost Stop-Loss in the S&P 500 - July 1988 to June 2011

A. Buy-and-Hold

Annualized Return(%)	9.49
Annualized Volatility(%)	18.16
Sharpe Ratio	0.31

B. Moving Average (0.2% Transactions Cost)

Moving Average Length (days)	10	25	50	100	150	200	250	300	350	400	450
Annualized Return(%)	-5.37	-0.21	2.53	4.32	6.48	7.68	8.63	9.50	10.05	10.50	9.50
Annualized Volatility(%)	11.54	11.17	10.88	11.11	11.34	11.52	11.72	12.06	12.16	12.33	12.35
Sharpe Ratio	-0.79	-0.36	-0.12	0.05	0.24	0.34	0.41	0.47	0.51	0.54	0.46

C. Moving Average Crossover (0.2% Transactions Cost)

M.A. Crossover Length (days/days)	25/50	25/100	50/100	50/150	50/200	100/250	100/300	100/350	100/400	150/300	150/350
Annualized Return(%)	3.37	5.45	8.04	9.23	7.45	6.38	6.70	10.83	6.29	10.88	10.30
Annualized Volatility(%)	11.18	11.24	11.53	12.03	10.56	7.70	9.18	12.67	9.07	12.62	12.64
Sharpe Ratio	-0.04	0.15	0.37	0.45	0.35	0.33	0.32	0.55	0.27	0.56	0.51

D. Breakout (0.2% Transactions Cost)

Breakout Length (days)	10	25	50	100	150	200	250	300	350	400	450
Annualized Return(%)	-0.97	3.95	5.28	8.83	9.27	10.61	11.19	10.54	8.81	9.14	8.24
Annualized Volatility(%)	11.33	10.71	10.64	11.26	12.01	12.21	12.53	12.55	12.29	12.56	12.25
Sharpe Ratio	-0.42	0.01	0.14	0.45	0.46	0.56	0.59	0.54	0.41	0.43	0.36

Table 6

End-of-Month Fundamental and Trend Following Methods in the S&P 500 - January 1952 to June 2011

Strategy (0.2% Transactions Cost)	Buy-and-Hold	Dividend Yield	Earnings Yield	Fed Model	GEYR	CAPE	TF (10MMA)
Annualized Return(%)	10.54	9.92	11.04	10.51	9.64	10.59	10.50
Annualized Volatility(%)	14.65	11.12	14.32	12.23	11.36	12.24	10.57
Sharpe Ratio	0.39	0.46	0.44	0.47	0.43	0.48	0.54