Original Article

Breaking into the blackbox: Trend following, stop losses and the frequency of trading – The case of the S&P500

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ABSTRACT In this article, 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 (MA) 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.
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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 (MAs) 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 (~10 months): if the current price is above (below) the MA, (or indeed perhaps the MA plus or minus a few percentage points around it to avoid 'whipsaw' trading), the rule gives a buy (sell) signal. In this article, we investigate a variety of trend-following models using the S&P500 with particular reference to a number of practical features that 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 MA, crossover, channel and breakout rules.

(ii) Is there any advantage in trading frequently, for example, 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.

In this article, we focus very much on a limited set of performance statistics for our chosen investment strategies, namely, mean return, volatility (standard deviation) and risk-adjusted return in the form of the Sharpe ratio. We also show higher moments for completeness, acknowledging that they may well vary substantially from those found in conventional buy-and-hold strategies. This emphasis simply reflects both primary investor interest and practitioner practice while comparing investment strategies, also using higher moments can be very challenging indeed.

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, whereas Rouwenhorst (1998) finds 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 *et al*, 2009; Moskowitz *et al*, 2010). However, both Korajczyk and Sadka (2004) and Lesmond *et al* (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, Miffre and Rallis, 2007; Szakmary *et al*, 2010).

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 on 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 *et al*, 2010; 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. In addition, 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, b) in reviewing nine 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. Hurst *et al* (2012) demonstrate that trend following has been a robust investment approach for over 100 years. They observe that following such a methodology, across a range of markets, generated substantial positive returns in every decade from 1903 to 2012.

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;

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

TREND-FOLLOWING RULES AND THE S&P500

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

(1) simple daily MAs, where the buy signal occurs when the S&P500's index value moves above the average; we consider MAs ranging from 10 to 450 days;
(2) MA crossovers where the buy signal occurs when the shorter duration average of the S&P500'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&P500'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, although 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 MA 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&P500 index over the relevant holding period; however, when the return 'says' do not invest we earn the return on cash (usually in the form of Treasury bills) over the relevant holding 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 MA crossover technique also smoothes the current observation with a shorter length MA, whereas acceleration or breakout signals emphasise even more on the distinction between a recent/current price move and recent past: sharp moves lead to stronger signals. We utilise daily S&P500 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 three classes of MA rules based on daily signals and trading, whereas Table 2 uses end-of-month rules and trading. For our purposes, a MA rule refers to the following: 'if on a given day the closing price is above the "*x*-day" MA, we earn the return on the S&P500 index over the following month; otherwise we earn the return on T-bills'. We present the passive holding of the S&P500 for comparison. Comparing daily with end-of-month decision rules in Tables 1 and 2, 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 per cent per annum, compared with a holding period return of 9.49 per cent and Sharpe ratio of 0.31 for the buy and hold, passive alternative. The best monthly MA rule in Table 2 is the 200-day rule with a return of 10.66 per cent 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; ap Gwilym *et al*, 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 MAs of 6–12 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: Daily trend-following methods in the S&P500 – July 1988 to June 2011

Buy and hold											
Annualised return (%)	9.49	–	–	–	–	–	–	–	–	–	–
Annualised volatility (%)	18.16	–	–	–	–	–	–	–	–	–	–
Sharpe ratio	0.31	–	–	–	–	–	–	–	–	–	–
Skewness	–0.62	–	–	–	–	–	–	–	–	–	–
Kurtosis	1.18	–	–	–	–	–	–	–	–	–	–
MA (0.2 per cent transactions cost)											
MA length (days)	10	25	50	100	150	200	250	300	350	400	450
Annualised return (%)	–5.37	–0.21	2.53	4.32	6.48	7.68	8.63	9.50	10.05	10.50	9.50
Annualised 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
Skewness	0.18	0.06	0.06	–0.03	–0.24	–0.23	–0.25	–0.33	–0.31	–0.09	–0.18
Kurtosis	1.79	0.78	0.89	0.37	0.53	0.63	0.96	2.10	2.31	1.91	1.83
MA crossover (0.2 per cent transactions cost)											
MA 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
Annualised return (%)	4.26	6.41	8.49	9.28	10.62	10.50	10.83	10.83	10.30	10.88	10.30
Annualised 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
Skewness	–0.40	–0.05	–0.46	–0.28	–0.19	–0.32	–0.18	–0.18	–0.20	–0.18	–0.17
Kurtosis	1.23	0.45	2.33	2.73	2.80	2.33	2.18	2.04	2.22	2.24	2.16
Breakout (0.2 per cent transactions cost)											
Breakout length (days)	10	25	50	100	150	200	250	300	350	400	450
Annualised return (%)	–0.53	3.95	5.90	8.44	9.27	10.61	11.19	10.54	9.52	9.58	9.18
Annualised 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
Skewness	–0.12	0.23	–0.02	0.18	–0.20	–0.21	–0.21	–0.31	–0.26	–0.28	–0.26
Kurtosis	2.49	0.73	0.80	0.70	2.60	2.61	2.08	2.34	2.41	2.14	2.55

Table 2: Trend-following methods in the S&P500 with only end-of-month trading – July 1988 to June 2011

Buy and hold											
Annualised return (%)	9.49	–	–	–	–	–	–	–	–	–	–
Annualised volatility (%)	18.16	–	–	–	–	–	–	–	–	–	–
Sharpe ratio	0.31	–	–	–	–	–	–	–	–	–	–
Skewness	–0.62	–	–	–	–	–	–	–	–	–	–
Kurtosis	1.18	–	–	–	–	–	–	–	–	–	–
MA (0.2 per cent transactions cost)											
MA length (days)	25	50	100	150	200	250	300	350	400	450	–
Annualised return (%)	4.58	6.19	7.06	8.48	10.66	10.72	9.98	10.68	10.74	11.19	–
Annualised 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	–
Skewness	–0.35	–0.12	–0.48	–0.53	–0.41	–0.28	–0.33	–0.21	–0.18	–0.18	–
Kurtosis	2.30	1.70	2.95	2.69	2.68	2.64	2.55	2.28	2.26	2.20	–
MA crossover (0.2 per cent transactions cost)											
MA 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
Annualised return (%)	7.69	6.84	8.03	8.74	10.45	11.13	10.56	10.89	10.37	10.89	9.92
Annualised 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
Skewness	–0.36	–0.31	–0.37	–0.23	–0.24	–0.20	–0.17	–0.19	–0.20	–0.19	–0.24
Kurtosis	3.24	2.77	2.95	2.86	2.79	2.23	2.20	2.13	2.27	2.24	2.23
Breakout (0.2 per cent transactions cost)											
Breakout length (days)	25	50	100	150	200	250	300	350	400	450	–
Annualised return (%)	5.50	7.43	8.00	10.60	11.38	11.59	10.51	9.37	9.54	9.48	–
Annualised 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	–
Skewness	–0.24	–0.34	–0.33	–0.19	–0.17	–0.22	–0.28	–0.26	–0.29	–0.29	–
Kurtosis	2.19	3.22	3.08	2.77	2.70	2.21	2.32	2.48	2.20	2.69	–

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 per cent) and Sharpe values (0.56) were achieved when we applied a 150/300-day crossover rule, although 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-day 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 per cent) 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 per cent, with Sharpe ratios of 0.61 and 0.62, respectively.

In summary we can say, first, 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 – MA, MA 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 MA rule using daily decision rules ranges from −0.79 to 0.54; the equivalent range for monthly decision making is 0.06–0.59. 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, although we have to be careful that such enthusiasm is possibly based solely on backward-looking historical analysis in which technical rules have been selected by a careful *ex–post* interaction of chosen sample period and model. It is well known that completely clean out-of-sample testing of technical models is very hard to achieve.

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 as 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 per cent and a Sharpe of 0.58, the latter being around 50 per cent 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 1–3, although covering different estimation periods, suggest that looking at the data only at the end of month may well be advantageous. Annaert *et al* (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

Table 3: End-of-month trend-following methods in the S&P500 – January 1952 to June 2011

Buy and hold										
Annualised return (%)	10.54	–	–	–	–	–	–	–	–	–
Annualised volatility (%)	14.65	–	–	–	–	–	–	–	–	–
Sharpe ratio	0.39	–	–	–	–	–	–	–	–	–
Skewness	–0.42	–	–	–	–	–	–	–	–	–
Kurtosis	1.78	–	–	–	–	–	–	–	–	–
MA calculated daily (0.2 per cent transactions cost)										
MA length (days)	25	50	100	150	200	250	300	350	400	450
Annualised return (%)	6.79	7.08	8.21	9.79	10.82	10.90	10.49	10.81	10.37	9.77
Annualised 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
Skewness	–0.51	–0.07	–0.67	–0.71	–0.51	–0.45	–0.46	–0.41	–0.43	–0.41
Kurtosis	5.69	2.15	5.95	5.88	5.75	5.31	5.17	4.81	4.61	4.43
MA calculated monthly (0.2 per cent transactions cost)										
MA length (months)	4	6	8	10	12	14	16	18	20	–
Annualised return (%)	6.95	9.28	10.14	10.50	11.01	10.62	10.98	10.77	10.56	–
Annualised 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	–
Skewness	–0.57	–0.68	–0.66	–0.61	–0.46	–0.47	–0.42	–0.42	–0.43	–
Kurtosis	5.58	5.96	5.78	5.58	5.35	5.13	4.92	4.76	4.62	–

be a role for stop-loss rules to improve the performance of a monthly based trading rule.

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 as this was synonymous with market efficiency and rationality 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. Acar and Satchell (2002) show there are theoretical reasons why stop-loss rules may affect higher moments relative to buy-and-hold strategies; they show that only symmetrical long/short strategies applied to a driftless random walk will keep the distributional characteristics unchanged. In most other cases, including long and neutral rules and combinations of strategies as presented here, the higher moments are likely to differ from buy and hold to a degree that may or not be significant. To that end, we present skewness and kurtosis statistics with each strategy.

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, as 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 and thus it is also important to compare portfolio variance, and indeed higher moments, 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 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 breakout and re-entry stop-loss rule, where the exit signals breaking through an 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 per cent. Clearly, both the returns and volatility rise with the stop loss through to a peak return at a stop loss of 12 per cent. 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&P500 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*.

FUNDAMENTAL METRICS VERSUS THE 10-MONTH TREND-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

Table 4: Using stop losses with daily trend-following methods in the S&P500 – July 1988 to June 2011

Breakout stop loss (0.2 per cent transactions cost)												
Opening/closing breakouts (days/days)	50/10	50/25	100/10	100/25	100/50	150/25	150/50	200/50	200/100	250/100	250/150	250/200
Annualised 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
Annualised 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
Skewness	0.06	0.52	0.62	0.02	–0.01	–0.03	–0.03	–0.08	0.20	0.21	–0.19	–0.19
Kurtosis	1.63	2.90	4.27	2.72	1.73	3.03	1.86	2.11	1.08	1.04	2.83	2.51
Percentage stop loss on 200-day breakout strategy (0.2 per cent transactions cost)												
Stop loss percentage	3	5	7	10	12	15	–	–	–	–	–	–
Annualised return (%)	3.02	4.47	6.82	9.52	10.13	9.61	–	–	–	–	–	–
Annualised 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	–	–	–	–	–	–
Skewness	0.45	0.02	0.10	0.07	0.03	–0.23	–	–	–	–	–	–
Kurtosis	2.45	2.37	2.36	1.96	1.72	2.86	–	–	–	–	–	–

Table 5: Daily trend-following methods with purchase cost stop loss in the S&P500 – July 1988 to June 2011

Buy and hold											
Annualised return (%)	9.49	–	–	–	–	–	–	–	–	–	–
Annualised volatility (%)	18.16	–	–	–	–	–	–	–	–	–	–
Sharpe ratio	0.31	–	–	–	–	–	–	–	–	–	–
Skewness	–0.62	–	–	–	–	–	–	–	–	–	–
Kurtosis	1.18	–	–	–	–	–	–	–	–	–	–
MA (0.2 per cent transactions cost)											
MA length (days)	10	25	50	100	150	200	250	300	350	400	450
Annualised return (%)	–5.37	–0.21	2.53	4.32	6.48	7.68	8.63	9.50	10.05	10.50	9.50
Annualised 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
Skewness	0.18	0.06	0.06	–0.03	–0.24	–0.23	–0.25	–0.33	–0.31	–0.09	–0.18
Kurtosis	1.79	0.78	0.89	0.37	0.53	0.63	0.96	2.10	2.31	1.91	1.83
MA crossover (0.2 per cent transactions cost)											
MA 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
Annualised return (%)	3.37	5.45	8.04	9.23	7.45	6.38	6.70	10.83	6.29	10.88	10.30
Annualised 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
Skewness	–0.43	–0.07	–0.57	–0.23	0.54	0.63	0.44	–0.18	0.39	–0.18	–0.17
Kurtosis	1.17	0.65	2.77	2.75	2.83	6.24	4.65	2.04	4.96	2.24	2.16
Breakout (0.2 per cent transactions cost)											
Breakout length (days)	10	25	50	100	150	200	250	300	350	400	450
Annualised return (%)	–0.97	3.95	5.28	8.83	9.27	10.61	11.19	10.54	8.81	9.14	8.24
Annualised 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
Skewness	–0.17	0.23	–0.09	0.24	–0.20	–0.21	–0.21	–0.31	–0.29	–0.28	–0.29
Kurtosis	2.41	0.73	0.97	0.65	2.60	2.61	2.08	2.34	2.71	2.45	2.77

Table 6: End-of-month fundamental and trend-following methods in the S&P500 – January 1952 to June 2011

Strategy (0.2 per cent transactions cost)	Buy and hold	Dividend yield	Earnings yield	Fed model	GEYR	CAPE	TF (10-month MA)
Annualised return (%)	10.54	9.92	11.04	10.51	9.64	10.59	10.50
Annualised 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
Skewness	–0.42	0.03	–0.25	–0.34	–0.88	–0.03	–0.61
Kurtosis	1.78	4.18	1.01	2.74	5.83	2.85	5.58

such as dividend and earnings' yields (Campbell and Shiller, 1998), the Fed model (ap Gwilym *et al*, 2006), the relative yield on bonds and equities (Clare *et al*, 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 1-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 article.

ap Gwilym *et al* (2006), using data from 1988 for six 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, although 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.

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 with 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.

Although an indisputable methodology for assessing the validity of back-testing trading rules has yet to be discovered, we believe that this should not constrain research in this area which is so important to many practitioners and investors; rather, it should emphasise the need for caution in interpreting our findings and the possible time dependency of any results. If anything, it also emphasises the need to revisit such findings at regular intervals and to subject any such findings to the closest scrutiny. In addition, we present higher moment statistics for each model, as it is known that they will generally be affected by both stop-loss rules and relative to the simple buy-and-hold default strategy.

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NOTES

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.
2. Lo *et al* (2000) provide evidence that algorithms implementing other popular patterns of technical analysis can provide incremental information for returns. Here, we concentrate on strategies that can be given a precise analytic form.
3. From Shiller's Website www.econ.yale.edu/~shiller/data.htm.

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