Why do Moving Average Rules Work? Comprehensive Evidence from World Markets

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Abstract

The ability of Moving Average rules to predict future stock market returns is well established in the finance literature but the underlying causes of this ability remain unexplained. In addition, the rules have not been reconciled with standard econometric models. We show that the ability of the rules to predict market direction is largely based on the existence of very short term trends in the data in which positive/negative daily returns are more likely to be followed by positive/negative returns. We find that the success of the rules is driven by short term market frictions rather than short term behavioral issues or any longer term phenomena. The relevant properties of the market are better captured by a simple Markov Chain model than by the autocorrelation statistic or standard autoregressive models. We initially confirm our results on the data used in the seminal paper of Brock, Lakonishok and LeBaron (1992). We subsequently confirm our findings on a number of other long series of market data and also on data from a comprehensive set of global markets.

Keywords: Technical analysis; Market Efficiency; Predictability; International

JEL classification: G11, G14, G15

1. Introduction

Technical analysis predicts future prices in financial markets using past price data and sometimes other data like trading volume. The method has long been used in financial markets (Park and Irwin, 2007; Lo and Hasanhodiz, 2010). Recent research finds that the vast majority of fund managers use technical analysis and it is preferred to fundamental analysis (Menkhoff, 2010).

The academic study of technical analysis also has a long history. Early empirical findings were rather negative regarding the profitability of various technical rules in stock markets (Cootner, 1962, Fama and Blume, 1966, Van Horne and Parker, 1967, 1968, James 1968, Jensen and Benington, 1970). However, some influential papers published in the early 1990s, particularly one by Brock, Lakonishok and LeBaron (1992), henceforth BLL, showed the approach in a more positive light. The study by BLL reported consistent and positive results about the forecasting power of technical trading rules and Moving Average (MA) rules in particular. The moving average (MA) rule is one of the most popular technical trading rules amongst practitioners, has been most extensively studied in the academic literature, and is the focus of our present study. The BLL study was impressive in its use of a long price history (90 years of the DJIA) and the application for the first time of the model-based bootstrap method. This paper has given rise to a very considerable literature investigating technical analysis from a variety of perspectives.

Numerous studies have examined MA rules in various world markets and generally found a good measure of support for their effectiveness. In the UK, Hudson et al. (1996) examine the rules on the FT30 from 1935 to 1994 and find results broadly similar to those of BLL. Metghalchi et al. (2012) examine the rules in 16 European stock markets from 1990 to 2006 and find that the simple MA rule has predictive power in all of the countries. Bessembinder and Chan (1995) find that the rules have explanatory power in five Asian markets with the rules having greater explanatory power in less developed markets. Ito (1999) investigates the trading rules in six Pacific-Basin countries. They find that the rules have predictive power in Japan, Canada, Indonesia, Mexico and Taiwan, but not in the US. Chen et al. (2009) find that technical trading rules can be profitable in eight Asian markets in a period from 1975 to 2006.

Several recent papers have shown that the rules tend to vary in their effectiveness over time. Shynkevich (2012) studies the performance of rules that are adjusted for data snooping bias on the technology industry and small cap sector portfolios from 1995-2010. They find that the MA rule only outperforms a buy-and-hold strategy over the first half of the sample. Fang et al. (2013) examine out-of-sample data from the DJIA and S&P500 which both pre-dates and post-dates the original BLL sample, and find no evidence of statistical predictability in any of the out-of-sample periods. Taylor (2014) studies the performance of the technical trading rules of BLL over the period 1928-2012 on all members of the DJIA. The study finds that the risk-adjusted profits available are confined to particular episodes primarily from the mid-1960s to mid-1980s, and that they rely on the ability of investors to short-sell stocks.

Although, the ability of the rules to predict market movements has been extensively documented this does not necessarily imply market inefficiency given trading costs and other market frictions. Bessembinder and Chan (1998) investigate the profitability of the rules by allowing for dividends and trading costs and find that the transaction costs outweigh the returns. Furthermore, Day and Wang (2002) re-examine the BLL findings adjusting for dividends, interest earned on the proceeds from short sales, transaction costs and the impact of non-synchronous prices and find that these adjustments eliminate risk-adjusted excess profits. Some interesting recent papers have, however, offered fresh insights into practical uses of technical analysis which do not necessarily depend on the ability to make direct trading profits. Neely et al. (2014) show that technical indicators match or exceed the ability of macroeconomic variables to forecast stock market returns. Zhu and Zhou (2009) show that MA rules add value to asset allocation rules that determine the proportions of wealth put into stocks. Han et. al. (2013) document that applying a moving average strategy to portfolios sorted by volatility substantially outperforms a buy-and-hold strategy.

The underlying reasons why MA rules can predict future price moves have not been well established although quite a number of models have either been specifically proposed or are clearly potentially relevant. Neely (2014) outline several classes of model that have been specifically proposed:

i) Models based on heterogeneity in the time taken for investors to receive information.

ii) Models based on heterogeneity in the reactions of investors to new information.

iii) Models based on underreaction or overreaction to information caused by behavioral biases.

iv) Models based on market sentiment.

In addition, other research which is clearly of potential relevance includes:

v) Underreaction to news because of trading costs (Ng et. al., 2007).

vi) Spurious trends caused by non-synchronous pricing (Day and Wang, 2002).

vii) Extrapolation of perceived trends in the data (Bloomfield and Hales, 2002.

Clearly, given the foregoing, there are quite a number of potentially relevant models which may, in addition, not be operating exclusively. The models can, however, be classified in a number of dimensions. One dimension is the length of time over which the underlying causal effects operate, another dimension is whether the model is driven by behavioral or rational factors. If we consider models based on the existence on very short term effects in the market (by very short term we would be looking at periods of, at the most, a handful of days) some models are based on delays in news being fully incorporated into prices for a variety of reasons and others are based on data reporting issues such as those related to non-synchronous trading. For convenience we can refer to these models as being based on the existence of short term market frictions and it is clear that they would tend to cause short term trends in the market. Other models propose that short term trends occur because of behavioral biases. Bloomfield and Hales (2002) present experimental evidence that investors tend to make erroneous predictions about the next step in sequences of returns even after being informed that the returns follow a random walk. In particular they show that the participants in their experiments have a strong tendency to predict trending in a way consistent with 'hot hands' biases (Gilovich et al., 1985).

Models based on the existence of long term effects tend to depend on behavioural biases such as under-reaction to news over a substantial period of time or the existence of extended periods where a particular type of market sentiment dominates. A priori, it is by no means clear whether short term or long term models are more appropriate as the moving average rules draw on relatively long term data to make predictions. This question seems an appropriate one to be answered empirically. Prior empirical evidence does not seem supportive of short term market friction models given the poor performance of conventional econometric models as detailed in the paragraph below.

Surprisingly little work has tried to reconcile the MA approach with more conventional econometric methods of explaining stock price movements. BLL show that the results from the MA rules are not consistent with bootstrap series generated by random walk, AR(1), GARCH-M and EGARCH time series models. These models are based on modelling returns based on returns in the preceding period so the results provide no support for short term friction models. To our knowledge, little work subsequent to that of BLL has been done in this area. Moving average rules are simple to calculate but potentially could capture complex stock dynamics that are difficult to model or not captured by conventional time series approaches. For example, a MA(150) rule incorporates, all the information contained in stock prices over the last 150 days and so could, in theory, be capturing extremely complex long term stock dynamics. Also a successful MA rule could potentially be explained by an almost infinite variety of underlying processes. So, overall, this is a rather daunting task for researchers.

Our paper makes a number of contributions to the literature. We show that the simplest possible trend following strategy, equivalent to a Markov chain based on market direction, will duplicate the signals from a moving average rule to a substantial extent. We further show that simple autocorrelation measures are not a good guide to the presence of very short term trends in stock market data. Given this, we show empirically that the *predictive* power of the rules in a period is almost entirely driven by the extent to which positive/negative daily returns in the market concerned are more likely to be followed by positive/negative daily returns. In practice, considering data from more than one time period in the past provides very little extra information so indicators of market direction effectively follow a simple Markov chain and the parameters of this determine how well an MA rule can predict. Thus we able to reconcile the MA rules with a standard econometric model.

We investigate some potential reasons for the observed short term trend continuance in an effort to arrive at fundamental explanations for the success of technical analysis. We show that there is little evidence to support short term behaviorial explanations based on extrapolation as discussed in Bloomfield and Hales (2002). Thus, it appears that the success of MA rules is largely driven by short term market frictions.

We confirm our arguments empirically on a wide range of data. We initially show that our arguments hold on the data used in the seminal BLL paper. Subsequently we analyse data using other indices and markets where very long term data is available and from a comprehensive set of global stock markets.

The remainder of the paper is organised as follows: Section 2 sets out our theoretical model and findings, Section 3 shows detailed investigation of the BLL results and their associated data. Section 4 uses logit models to further investigate the causes of the effects we observe. Section 5 investigates a wide selection of other data. Section 6 presents conclusions.

2. Theoretical Motivation and Findings

In this section, we firstly present the definition of the MA rule which was applied in BLL and numerous subsequent studies. Next, in sub-section 2.2 we present a simple general model which is compatible with the prior models seeking to explain the success of MA rules which appear in the literature. In sub-section 2.3 we show that the simplest possible trend following strategy will duplicate the signals from a moving average rule to a substantial extent. In sub-section 2.4 we show that simple autocorrelation measures are not a good guide to the presence of very short term trends in stock market data. Finally in sub-section 2.5 we summarise our theoretical findings.

2.1. Definition of the Moving Average (MA) rule

A moving average is an average of the level of an index, or other financial instrument, over a number of consecutive time periods up to the present date. The standard MA rule generates buy (sell) signals when a moving average based on a short period is above (below) a moving average based on a long period. Thus the buy signal is generated according to the following formula:

$$\left[\sum_{\lambda=1}^{S} P_{t-(\lambda-1)} \Big/ S\right] > \left[\sum_{\lambda=1}^{L} P_{t-(\lambda-1)} \Big/ L\right] + band \;\Rightarrow Buy\ at\ time\ t \qquad (1)$$

Where P_t is the price at time t. Sell signals are generated when the inequality is reversed:

$$\left[\sum_{\lambda=1}^{S} P_{t-(\lambda-1)} \Big/ S\right] < \left[\sum_{\lambda=1}^{L} P_{t-(\lambda-1)} \Big/ L\right] - band \Rightarrow Sell\ at\ time\ t \qquad (2)$$

A percentage band may be included to reduce the number of signals by eliminating "whiplash" signals when the short and long period moving averages are close[1]. The normal

[1] Generally a 1% band is used in the literature.

notation adopted for a moving average rule with a short period average of S, a long period average of L and a band of 1% is (S,L,b). Popular MA rules in the literature are (1,50,0), (1,100,0) and (1,200,0). Shorter moving averages follow the market closely, whereas longer moving averages smooth market fluctuations. Thus a rule with $S = 1$ is very responsive, that is, gives buy (sell) signals whenever the actual returns rise above (below) the moving average.

2.2. An Inclusive Model of Moving Average Rules

We propose a simple inclusive model based on the common features in the models which have been previously proposed to provide explanations for the success of MA rules based on short term market frictions.

Taken the common features of the models proposed, and indeed combinations of them, we can assume that:

$$r_t = f(r_{t-1},\ r_{t-2},\ldots,\ r_{t-k}) + \varepsilon_t \qquad (3)$$

Now the particular functional form of f is largely unknown and possibly time varying as is the distribution of ε_t. However, we do have the knowledge that all the models based on short term effects would predict short term trend continuance. In the limit, the simplest version of (3) that would fit this criteria is:

$$\begin{aligned} &\Pr(\, r_t \geq 0 \mid r_{t-1} \geq 0) > \Pr(\, r_t < 0 \mid r_{t-1} \geq 0) \\ &\Pr(\, r_t < 0 \mid r_{t-1} < 0) > \Pr(\, r_t \geq 0 \mid r_{t-1} < 0) \qquad (4) \end{aligned}$$

That is the trends do not last for longer than one day. This is a fairly plausible supposition in regards to market friction effects which are only likely to be important in the very short term although it is certainly possible that there may be friction effects over a longer period. In this context this issue of how long trends may last can be investigated empirically. We initially check the properties of a model based on (4) to see if it can provide a reasonable explanation for the performance of MA rules.

By doing this we are taking a tractable approach starting with an underlying process and see if it is compatible with a successful MA rule. This indeed was the approach attempted by

BLL albeit unsuccessfully. Our set up in (4) is actually a Markov chain process where a positive/negative return on day t-1 is more likely to be followed by a positive/negative return on day t.

2.3. Discussion showing that a Moving Average Rule will give similar signals to those from a trivial trend following rule.

We show that the moving average rule will give similar signals to those from a simple Markov Chain which gives buy/sell signals based on the direction of the previous day's return. We adopt some simplifying assumptions without loss of generality.

Initially consider a series where a positive return r_t on day t is denoted by 1 and a decrease in price is denoted by -1. Also define MA(t) as the average return (equivalent to the average price if starting price is 0) over the L days up to the end of day t and define Sum(t) as the sum of the returns over the last L days (equivalent to the latest price if the initial price was 0). In this setting the moving average rule gives a buy signal for day t+1 if Sum(t) ≥ MA(t) and a sell signal if Sum(t) < MA(t).

Now assume we know the underlying true nature of the returns is such that a positive/negative return on day t is more likely to be followed by a positive/negative return on day t+1. Say, for example, we chose parameters matching those in the BLL data so that $P(r_{t+1}=1|r_t = 1) = 0.55$, $P(r_{t+1}= 0|r_t = 1) = 0.45$, $P(r_{t+1}=1|r_t = 0) = 0.45$, $P(r_{t+1}=0|r_t = 0) = 0.55$. Given this knowledge the optimal trading rule is simply to buy at the end of day t when the return on day t has been positive and sell when the return has been negative.

The point of this subsection is to consider the extent to which the moving average rule would provide the same buy/sell signals as the optimal trading rule.

Now consider the situation at the end of day t-1 after observing the return on that day.

If day t has a positive return

$\text{Sum}(t) = 1 + \text{Sum}(t\text{-}1) – r_{t-50}$

Now r_{t-50} either takes the value 1 or -1.

Thus $\text{Sum}(t) \geq \text{Sum}(t\text{-}1)$

$\text{Sum}(t) = \text{Sum}(t\text{-}1)$ if $r_{t-50} = 1$

$\text{Sum}(t) = \text{Sum}(t\text{-}1) + 2$ if $r_{t-50} = -1$

Now Ave(t) = l/L + Ave(t-1) - r_{t-50}/L

Now r_{t-50} either takes the value 1 or -1.

Thus Ave(t) ≥ Ave(t-1)

Ave(t) = Ave(t-1) if $r_{t-50} = 1$

Ave(t) = Ave(t-1) + 2 if $r_{t-50} = -1$

Overall if there was a buy signal according to the moving average rule at the end of day t-1 i.e. Sum(t-1) ≥ Ave (t-1) then at the end of day t there will still be a buy signal. So the signal from the moving average rule is the same as from the optimal trading rule.

By symmetry if the return on day t is negative and the moving average rule was giving a sell signal at the end of day t-1 both the optimal rule and the moving average rule would coincide and give a sell signal at the end of day t.

A more complex scenario is when the return on day t is positive but the moving average rule was giving a sell signal at the end of day t-1. The optimal rule would give a clear buy signal at the end of day t but the moving average would not necessarily give a buy signal as the signal would depend on the history of returns over the last L days ending at the end of day t.

If $r_{t-50} = 1$ then Sum(t) = Sum(t-1) and Ave(t) = Ave(t-1) so we would still have a sell signal so in this case the moving average return rule would give a different signal from the optimum rule.

If $r_{t-50} = -1$ then Sum(t) = Sum(t-1) +2 and Ave(t) = Ave(t-1) + 2/L

So Sum increases by a greater amount than average so the signal given by the moving average rule may change from sell to buy.

This can be quantified in this setting. The underlying process is a Markov chain with two possible states S = {-1, 1} and transition matrix:

$$P= \begin{bmatrix} 0.55 & 0.45 \\ 0.45 & 0.55 \end{bmatrix}$$

Now in this case the chain is reversible as P is symmetric. Also over time the chain rapidly converges to a limiting distribution of $\begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix}$

So we can make an accurate approximation of the series as a random walk. If we consider the case where L = 50 the moving average signal will change from a sell to a buy if an increase of 98/50 in Sum(t-1) increases it sufficiently to be over Ave(t-1).

Now we can model the last 50 returns as a simple discrete random walk with equal probabilities of up or down movements.

The expectation of the sum after 50 days is 0 and the variance is 50 giving a standard deviation of 7.07.

The sum and average of a set of outcomes over 50 days will be related, albeit in a complex way, depending on the sequence of the outcomes. A closed form relationship between the sum and average is unlikely to be derivable so numerical approximations are necessary. As a rough approximation the absolute value of the average of any particular sample will be approximately half the absolute value of the sum with both quantities having the same sign so if the sum is positive/negative the average will be positive/negative. Thus the difference between the sum and average will have a standard deviation in the region of around 3.5. In the scenario we are considering we know that sum is less than average so it is very likely that both are negative. In this context, an increase of 98/50 in the sum is about 0.56 of a standard deviation which will have a fairly substantial effect of the probability of a change in the moving average signal from sell to buy. From normal tables around 21% of moving average signals would change.

By symmetry in the final scenario when the return on day t is negative but the moving average rule was giving buy signal at the end of day t-1 about 21% of the time the moving average rule would change to a sell signal at the end of day t and thus match the best possible rule based on the return on day t.

In summary, we see four equally likely scenarios in two of them the moving average rule signal would match the signal given by the return on the last day and in the other two the rules would match about 20% of the time. So overall the signals given by the rules would match approximately 60% of the time.

Given the assumptions in some of the reasoning above we confirm our findings by randomly simulated 10,000 series with a 50 day moving average rule and found its trading signals matched those given by a rule based on the last return day in the series 59% of the time so our estimate seems reasonable.

2.4. Trivial Trend Following and Autocorrelation

We show that simple autocorrelation measures are not a good guide to the presence of very short term trends in stock market data. Simple measures of autocorrelation tend to underestimate the extent of short term trends. For example, if we initially consider a series of binary returns, as in sub-section 2.2 above, where each day is classified as having either a positive or negative return where the probability of a positive return after a positive return is 0.55 and the probability of a negative return after a negative return is also 0.55. One thousand simulations of a series of 25,042 observations, equal in length to the BLL study, give an average autocorrelation measure of 0.0984. In contrast, one thousand simulations of series of the same number of observations which are constructed so that the daily returns follow a N(0,1) distribution but the probability of a positive return after a positive return is 0.55 and the probability of a negative return after a negative return is also 0.55 give an average autocorrelation measure of 0.0653. Thus the intrinsic variability in daily stock returns tends to result in a lower autocorrelation measure than would be calculated from a binary series of positive and negative returns which is relevant for capturing trends in the data.

2.5. Summary of theoretical motivations and findings

In summary, we see that a very convenient way to understand moving average rules is to model them using simple trend following rules such as a basic Markov chain rule. Apart from its appealing simplicity, this approach has the advantage of being much better linked to other areas of academic research enabling deeper insights into the underlying causes of the success of the rules. We show that the Markov chain approach has some promise in explanatory terms as it will give similar buy and sell signals to a moving average rule. In contrast, autocorrelation measures are not likely to be a reliable guide to the likely effectiveness of moving average rules.

Whilst we have highlighted many potential advantages of the trend following (Markov chain) approach it is ultimately an empirical question as to whether it can model moving average rules sufficiently well. In the following sections we examine the data used in the seminal BLL paper and also data from other long data series and a comprehensive set of world stock markets.

3. Detailed Analysis of BLL Results

As discussed above the BLL paper is the most seminal contribution in this literature and shows results strongly supporting the effectiveness of MA rules. Thus if our proposed approach is to be useful it should show impressive results on the data used by BLL. We are able to very closely duplicate the results of BLL as shown in row (1) of table 1. For demonstration purposes we concentrate on the MA(1,50,0) rule.

One of our hypotheses is that the ability of rules to predict market direction should depend on short term trends in the price series. We check this very directly by creating an index removing the magnitude of returns from the original index by assuming an initial index of 100 and assuming an increase of 1% if the Dow increased on that day and -1% if the Dow decreased. This retains the original trends in the index but removing any return magnitude effects. This approach has clear parallels with the Markov chain approach discussed above. For convenience we have called this new index a directional index.

Row (2) of table 1 shows the results of applying the MA(1,50,0) rule to the directional index. The results are remarkably similar to the original BLL results in terms of the proportion of the days with a buy/sell signal being greater than 0, the t stats testing the returns on buy/sell days and the probability of returns of returns on days with buy/sell signals. In this case we can't interpret the magnitude of returns in a meaningful way other than to note that the mean given a buy signal is significantly positive and that given a sell signal is significantly negative. Overall the rule can very effectively predict future market direction from the previous directions of returns without reference to return size.

We further test our hypothesis that the direction of return on day t-1 should be a good predictor of the success of the MA rule in predicting the return on day t. In row 3 of Table 1 we see the effect of applying the MA(1,50,0) rule in the normal way to the Dow except that for a buy/sell trading signal to be given the previous days return has to be negative/positive. Thus the return on the previous day can be seen as being opposite to any trends or other information that may exist over the previous 50 days. It is very striking that this rule works 'in reverse' with the average return on days with a buy signal being significantly smaller than the average return on days with a sell signal and a substantially larger proportion of returns being positive on days with a sell signal than on days with a buy signal. The total number of buy and sell days is lower than for the preceding rows of the table because a substantial number of days are associated with neither buy nor sell signals. Row 4 of Table 1 shows the results of the same trading rule applied to the directional index. Qualitatively the results are very similar with similar proportions of correct buy and sell signals and levels of significance. The results associated with this trading rule clearly shows that effect of the return on day t-1 clearly outweighs that of the MA rule in terms of predicting the next price movement.

In row 5 of table 1 we show the outcome of applying a rule to the Dow index where a buy/sell signal is generated by a positive/negative return on the previous day[2]. We see the results are substantially stronger and more significant in all respects than those generated by the MA(1,50,0) rule. Row 6 of table 1 shows the results of the same trading rule applied to the directional index. Qualitatively the results are again very similar to those obtained from applying the trading rule to the full Dow index with similar proportions of correct buy and sell signals and levels of significance.

In row 6 of table we show the outcome of applying the normal MA(1,50,0) rule to the residuals after fitting an AR(1) rule to the index. The rule produces results that are only slightly worse than when it is fitted to the original index. This supports the finding of BLL that the rules are not primarily driven by autocorrelation.

In this section we have shown that on the data used in the BLL paper the trend following (Markov chain) approach seems highly associated with, and in effect explains, the MA approach. In isolation it considerably outperforms the MA rule and when the MA rule is adjusted to take account of the short term trend following inherent in the Markov rule it becomes so ineffective it actually makes predictions that are significantly incorrect. Our findings using a directional index adjusted to remove the magnitude of returns also strongly support the idea than the predictive power of the rules are driven by short term trends in market direction.

The only potential practical benefit to investors of following the MA rule rather than the Markov chain rule is that it tends to result in less trading so trading costs would be lower. But this is somewhat of an accidental by-product of the properties of the rule. Given the greater predictive power of the Markov chain rule, it would be possible to modify it to have less trading activity so it would dominate the MA rule.

[2] This rule is actually equivalent to a MA(1,2,0) rule but is more conveniently framed as a trend following rule

4. Logit analysis to examine the existence of trends and other patterns in the past data and their causes

If we model the trends in the market on a purely directional basis, that is, distinguishing between rises and falls using a binary variable it is appropriate to apply a standard logit approach. We can use the logit approach to determine the factors affecting the probability of a positive daily return (by symmetry similar factors would apply if we consider negative daily returns.

We use the formula $\Pr(r_t > 0|x_i, B) = \frac{e^{-\bar{x_i} B}}{\left(1-e^{-\bar{x_i} B}\right)}$

Where x_i is a set of characteristics which may explain the sign of r_t.

Initially we can explore the persistence of trends and other patterns in the data by setting the x_i's to be a set of 50 dummy variables $D_{t-1,}$ $D_{t-2,\ldots,}$, D_{t-50} ,where D_{t-k} is set to 1 if $r_{t-k} > 0$ and 0 if $r_{t-k} \leq 0$. By using this set of explanatory variables we can make some meaningful comparisons with a MA rule based on the previous 50 days of data. Our results are shown in Table 2.1. As expected from our previous analysis, the coefficient of D_{t-1} is positive and very highly significant indicating that positive returns are significantly more likely to be followed by positive returns. There seems little evident pattern associated with the lags beyond 3. The large majority of coefficients are not significant, the ones that are significant are only marginally so and there seems a good deal of randomness in the number of lags associated with the significant coefficients and also the sign of the coefficients in general. The coefficient of D_{t-2} is interesting as it is negative and highly significant. This indicates that the sign of returns at day t tend to be opposite to those at day t-2 even though they tend to be of the same sign of those at day t-1. One implication of this is that it is not going to optimal to base trivial trend following strategies on trends that last for more than one day. Of course, it would be possible to design trading rules to take advantage of this particular feature of the data and indeed create hypotheses to explain it but this would be departing from the main rationale of our paper. Overall the results shown in table 2 confirm that a one day market trend is highly effective in predicting market direction and looking at longer periods of past data is unlikely to be helpful.

We can further use Logit analysis to investigate some of the other features of the data and potential causes of the effect. This type of analysis is ideal to check the possibility drawn from Bloomfield and Hales (2002) that investors may calculate the probability of short term trends continuing from the incidence of trend reversal in the previous few days. We refit the logit model 3 times with $x_1 = D_{t-1}$ in all cases and x_2 set to be the number of trend reversals in the last 8, 16 and 30 days respectively (these parameters are taken from Bloomfield and Hales (2002)). The results shown in table 2.2 provide very little support for the hypothesis. Whilst the coefficients of the number of reversals are negative as expected none of them are significant at conventional significance levels.

A number of papers subsequent to BLL have shown a decline in the effectiveness of the MA rules. We check whether there is any decline during the period covered by BLL by fitting a time trend to the data. We refit the logit model with $x_1 = D_{t-1}$ and x_2 set to be the number of days elapsed from the start of the series. The results are shown in table 2.3. The time trend has a negative coefficient but not at a significant level so there is no strong evidence of a decline in the effect over time.

5. Detailed Analysis of Long Term Indices

We confirm our findings using data from the complete series of the DJIA, including the period after the BLL paper, and also data from other stock market indices with a long run of historic data. In particular, we additionally look at the S&P500 from the US, and the FT30 and FTSE All-share index from the UK. The use of different indices helps to guard against data mining and also brings in the effects of different market settings, different types of companies and different methods of index calculation.

Table 3 shows the results of applying the conventional rules to the DJIA. We show the same rules as BLL although we have tested many other rules have been tested and found them to be broadly consistent with those shown. The rules with long moving average periods of 50, 150 and 200 days when applied to the full data series all give very strong and significant results. However, the 2 day long moving average rule, which is equivalent to a Markov chain. does substantial outperform the long moving average period which is consistent with the earlier discussion. The results of applying the 150 day moving average rule to the data series divided into five quintiles are also shown in the table. The first three quintiles are significant, the fourth quintile is positive but not significant and the fifth quintile gives results that are actually negative albeit not significant. The 2 day long moving average rules, however, give much stronger results over the first four quintiles.

Table 4 shows the results of applying modified rules to the DJIA such the buy/sell signals generated as normal except the previous days return has to be negative/positive. In all cases the sign of the returns is reversed to a highly significant degree.

Table 5 gives results for the full data series of the S&P. Broadly the pattern of the results are very similar to those of the DJIA with the conventional rules generally being effective but the 2 day long moving average rules being by far the strongest. The modified rules again show reversed results

Table 6 gives results for the full data series of the FT30. Again the pattern of the results is very similar to those of the DJIA. The conventional rules are generally effective with the 2 day long moving average rules being the strongest by a large margin. The modified rules again show reversed results.

Table 7 gives results for the full data series of the FTSE. The familiar pattern of results is apparent. The conventional rules are highly effective with the 2 day long moving average rules being the strongest by a large margin. The modified rules again show reversed results.

6. Comprehensive Analysis of World Markets

6.1. Data

We confirm our findings using data from world stock markets. The data used is daily data from 36 country indices from around the world. The indices represent the major markets in these countries and consist of 20 developed markets and 16 developing markets in order to determine how the MA rule has behaved in each market type. The data period runs from 3rd October 1994 to 30th September 2014 generating 528 observations in each index. The daily returns for each index is calculated as the difference in log index values. Table 8 shows the basic descriptive data for the different markets studied and on an individual country basis, we find that each market has a positive mean return except Japan, which experiences a negative mean return over our full sample. Turkey has the largest positive mean return while Greece has the smallest positive mean return. Regarding standard deviations, we find that Turkey has the largest and New Zealand the least volatility of the markets studied. Most markets are negatively skewed, while all have excess kurtosis of differing levels. All markets have large and significant Jarque-Bera statistics indicating the non-normal nature of the returns. We also find that developing markets as a whole have a larger mean return than developing markets and a larger standard deviation of returns.

6.2 Results

In this section we initially present the results of applying the standard rules in the different markets. Then we conduct our analysis of the reasons for the success of the rules.

6.2.1 Rule Profits

Tables 9 and 10 report the MA rule results on the developed markets where all developed markets generate a positive buy-sell difference except the 1-50 rule in the US. Austria, Belgium, Ireland, Japan, Portugal and Singapore all generate at least 2 statistically significant buy-sell differences at the 5% level indicating the predictive power of the MA in these markets. All developed markets generate mean buy (sell) returns that are positive (negative) as should be the case with the MA rule. The developing markets MA results are presented in Table11 where we find that all MA rules generate positive buy-sell differences. Further, only Mexico, SK, Thailand and Turkey fails to generate at least 2 statistically significant at the 5% level buy-sell differences, indicating the significant predictive ability of the MA in developing markets. Further, a number of mean buy and mean sell returns are statistically significant. In total, 28.33% of the rules generate significant buy-sell differences in developed markets, while 66.67% of the rules generate significant buy-sell differences in developing markets indicating the high predictive power of the MA in developed markets compared to developing markets.

6.3. Analysis of the reasons for the effectiveness of the rules

6.3.1 Time Series Analysis

In line with the preceding discussion in section 3 we initially apply a trivial trend following rule to all the markets where a buy/sell signal is generated by a positive/negative return on the previous day. The results are shown in Table 12. For the developed countries the rule produces better average returns than the MA(1,50,0) rule in 13 out of 20 cases (binomial: nearly sig at 5% level) or if we consider only cases where the MA(1,50,0) is significant in 9 out of 12 cases (sig at 5% level). For the developing markets the rule produces better average returns than the MA(1,50,0) rule in 13 out of 16 cases (probably sig at 1% level) or if we consider only cases where the MA(1,50,0) is significant in 12 out of 15 cases (sig at 1% level).

We further investigate the effect of applying the MA(1,50,0) rule in the normal way to each index except that for a buy/sell trading signal to be given the previous days return has to be negative/positive. The results are shown in Table 13. In 31 out of 39 cases the average return given by the rules reverse direction compared to the standard MA(1,50,0) rule (sig at a very high level). In nearly all cases the standard MA(1,50,0) rule gave a positive return and the modified rule a negative return. Interestingly, for the US the standard MA(1,50,0) rule gave a negative return and the modified rule a positive return.

Overall the results of our time series analysis provide very strong support for the proposition that the results of the moving average rules are being driven by very short term trends in the data.

7. Summary and Conclusions

In the paper we advance the literature on the causes of technical analysis by both theoretical analysis of the underlying formulae and empirical analysis of long term data sets from the US and other countries and more recent data from a comprehensive set of countries.

We show that the performance of the MA rules can be substantially explained by a very simple short term trend following strategy equivalent to a Markov chain rule based on market direction. The predictive power of the rules in a period is almost entirely driven by the extent to which positive/negative daily returns in the market are more likely to be followed by positive/negative daily returns. This feature is not well captured by the standard autocorrelation statistic.

We subsequently investigate the reasons for the observed short term trend continuance in an effort to arrive at more fundamental explanations of reasons for the success of technical analysis. Having ruled out short term behavioral explanations it appears that short term market frictions are the main explanation for the success of the MA rules.

We confirm our arguments empirically on a wide range of data. We initially show that our arguments hold on the data used in the seminal BLL paper. Subsequently we analyse data using several other long term data sets and from a comprehensive set of countries. Having shown the profitability of technical analysis in most of the countries, we empirically confirm our findings that the existence depends on the existence of short term trends in the data.

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Table 1: Moving Average Rules (1,50,0) – Data period 1897 to 1986

	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Pr (Buy = Sell = 0.5)	Buy-Sell
Duplicating BLL on full Dow index (1)	14381	10609	0.00050 (2.975)	-0.00028 (-3.642)	0.5393	0.4974	0.0000	0.00078 (5.424)
Results on directional index (2)	14370	10620	0.00070 (3.082)	-0.00006 (-3.769)	0.5376	0.4997	0.0000	0.00076 (5.935)
Rule on the full Dow index where a buy/sell signal is generated in the normal way except the previous days return has to be negative/positive (3)	5810	4558	-0.00021 (-2.2642)	0.00056 (1.9353)	0.5102	0.5366	0.982638	-0.00077 (-3.5634)
Rule on the directional index where a buy/sell signal is generated in the normal way except the previous days return has to be negative/positive (4)	5628	4292	0.00013 (-1.808)	0.00079 (2.2607)	0.5089	0.5419	0.9954	-0.00066 (-3.268)
Rule on the full Dow index where a buy signal is generated by a positive return on previous day (5)	13186	11804	0.00082 (5.7180)	-0.00057 (-6.156)	0.5513	0.4882	0.0000	0.00139 (10.219)
Rule on the directional index where a buy signal is generated by a positive return on previous day (6)	13034	11956	0.00098 (5.5494)	-0.00027 (-5.878)	0.551	0.4889	0.0000	0.00125 (9.914)
Rule on index residuals after AR(1) has been fitted (7)	14381	10609	0.00044 (2.4164)	-0.00021 (-2.959)	0.537	0.5034	0.0000	0.00065 (4.399)

Table 2: Logit Regressions showing the factors affecting the probability of a positive return on day t.

2.1 Past 50 days data: Dependent Variable: Prob(r_t > 0)

Variable	Coefficient	z-Statistic
C	-0.459671	-5.659694
D_{t-1}	0.257306	10.05777
D_{t-2}	-0.148343	-5.784755
D_{t-3}	0.012810	0.499432
D_{t-4}	0.053623	2.091111
D_{t-5}	0.062153	2.423559
D_{t-6}	0.002397	0.093444
D_{t-7}	-0.055215	-2.152396
D_{t-8}	0.023378	0.911320
D_{t-9}	0.010101	0.393790
D_{t-10}	0.035315	1.376813
D_{t-11}	-0.001611	-0.062790
D_{t-12}	0.058003	2.261260
D_{t-13}	0.000392	0.015270
D_{t-14}	0.021736	0.847353
D_{t-15}	0.054809	2.136884
D_{t-16}	0.028747	1.120558
D_{t-17}	-0.047296	-1.843336
D_{t-18}	0.034134	1.330387
D_{t-19}	0.020727	0.807960
D_{t-20}	0.051882	2.022671
D_{t-21}	0.018284	0.712733
D_{t-22}	0.017402	0.678364
D_{t-23}	0.039504	1.540164
D_{t-24}	0.037745	1.471558
D_{t-25}	0.004672	0.182128
D_{t-26}	0.018812	0.733309
D_{t-27}	-0.002444	-0.095262
D_{t-28}	0.046805	1.824821
D_{t-29}	0.050071	1.952166
D_{t-30}	0.026076	1.016475
D_{t-31}	-0.054892	-2.139541
D_{t-32}	0.061211	2.385934
D_{t-33}	0.015824	0.616783
D_{t-34}	0.016336	0.636754
D_{t-35}	0.031177	1.215270
D_{t-36}	0.019853	0.773933
D_{t-37}	0.030043	1.171172
D_{t-38}	0.013869	0.540657
D_{t-39}	0.017994	0.701514
D_{t-40}	0.028528	1.112158
D_{t-41}	0.012917	0.503579
D_{t-42}	0.047556	1.854037
D_{t-43}	0.026417	1.029792
D_{t-44}	-0.020771	-0.809702
D_{t-45}	0.046057	1.795608
D_{t-46}	-0.001381	-0.053854
D_{t-47}	-0.026986	-1.052155
D_{t-48}	-0.008906	-0.347214
D_{t-49}	0.062895	2.454042
D_{t-50}	-0.001687	-0.065932

2.2 Effect of number of recent reversals

Dependent Variable: Prob($r_t > 0$)

Variable	Coefficient	z-Statistic
C	-0.014109	-0.373494
D_{t-1}	0.251567	9.914208
REVERSALSLAST8DAYS(-1)	-0.009454	-0.937109

Variable	Coefficient	z-Statistic
C	0.032910	0.635269
D_{t-1}	0.251164	9.896398
REVERSALSLAS16DAYS(-1)	-0.011098	-1.609241

Variable	Coefficient	z-Statistic
C	0.004245	0.060230
POS_RET(-1)	0.250552	9.869026
REVERSALSLAST30DAYS(-1)	-0.003450	-0.713213

2.3 Time trend in BLL data

Dependent Variable: Prob($r_t > 0$)

Variable	Coefficient	z-Statistic
C	-0.014187	-0.495012
POS_RET(-1)	0.250568	9.875977
TIME	-2.43E-06	-1.383801

Table 3 – Dow Jones – conventional moving average rules

short	long	band	n.buys.	n.sells.	meanbuy	buyt	meansell	sellt	avret	tstat
Dow Jones Full Series										
1	50	0	21170	15046	0.04173	7.112	0.01496	1.417	0.05669	5.499
1	50	0.01	17184	11367	0.05059	7.717	0.01965	1.485	0.07024	5.817
1	150	0	22331	13785	0.03493	6.119	0.00941	0.831	0.04434	4.516
1	150	0.001	22141	13566	0.03518	6.131	0.00900	0.785	0.04418	4.486
1	200	0	22869	13197	0.03435	6.107	0.01063	0.905	0.04498	4.598
1	200	0.001	22713	13011	0.03473	6.152	0.01035	0.872	0.04509	4.599
1	2	0	19001	17258	0.06309	8.922	0.03129	3.592	0.09439	8.627
1	2	0.001	14688	13137	0.07942	9.446	0.03616	3.397	0.11558	8.802
Dow Jones First Quintile										
1	150	0	4813	3975	0.0264777	2.299	0.0166717	0.977	0.0431494	2.212
1	2	0	4598	4334	0.0418234	3.254	0.0279559	1.851	0.0697793	3.556
Dow Jones Second Quintile										
1	150	0	9885	6068	0.0418668	4.753	0.0256549	1.415	0.0675217	4.060
1	2	0	8564	7537	0.0851533	7.759	0.0593961	4.252	0.1445495	8.348
Dow Jones Third Quintile										
1	150	0	13206	6807	0.0328477	5.023	-0.010009	-0.684	0.0228386	2.775
1	2	0	10587	9574	0.0786424	9.405	0.0363148	3.527	0.1149572	8.916
Dow Jones Fourth Quintile										
1	150	0	8857	4586	0.0298478	3.499	-0.015116	-0.764	0.0147321	1.652
1	2	0	7066	6524	0.0612557	5.509	0.0141363	1.045	0.075392	4.445
Dow Jones Fifth Quintile										
1	150	0	5241	2170	0.0169902	1.504	-0.053029	-1.481	-0.036039	-0.266
1	2	0	4023	3536	0.0211126	1.320	-0.041169	-1.954	-0.020056	-0.616

Table 4 – Dow Jones – Modified Moving Average Rules

short	long	band	n.buys.	n.sells.	meanbuy	buyt	meansell	sellt	avret	tstat
Dow Jones Full Series: buy/sell signal generated as normal except the previous days return has to be negative/positive										
1	50	0	8608	6460	-0.002599	-0.268	-0.046704	-3.087	-0.049303	-2.520
1	50	0.001	8422	6257	0.0012866	0.132	-0.049546	-3.196	-0.048259	-2.351
1	150	0	9707	6346	-0.007746	-0.840	-0.055101	-3.547	-0.062847	-3.191
1	150	0.001	9619	6224	-0.007944	-0.857	-0.055967	-3.544	-0.063912	-3.201
1	200	0	10070	6140	-0.008294	-0.918	-0.054528	-3.405	-0.062822	-3.122
1	200	0.001	9999	6051	-0.007406	-0.815	-0.055548	-3.428	-0.062954	-3.069
1	2	0	0	0	NaN	NaN	NaN	NaN	NaN	NaN
1	2	0.001	0	0	NaN	NaN	NaN	NaN	NaN	NaN
Dow Jones First Quintile: buy/sell signal generated as normal except previous days return has to be negative/positive										
1	150	0	2092	1826	0.0034657	0.190	-0.036526	-1.560	-0.03306	-1.038
Dow Jones Second Quintile: buy/sell signal generated as normal except previous days return has to be negative/positive										
1	150	0	4208	2799	-0.035079	-2.413	-0.055725	-2.250	-0.090804	-3.284
Dow Jones Third Quintile: buy/sell signal generated as normal except previous days return has to be negative/positive										
1	150	0	5792	3126	-0.014785	-1.410	-0.106878	-5.305	-0.121664	-4.799
Dow Jones Fourth Quintile: buy/sell signal generated as normal except previous days return has to be negative/positive										
1	150	0	3943	2092	0.0057972	0.427	-0.091648	-3.324	-0.085851	-2.146
Dow Jones Fifth Quintile: buy/sell signal generated as normal except previous days return has to be negative/positive										
1	150	0	2322	1015	0.022551	1.221	-0.027825	-0.578	-0.005274	0.371

Table 5 – S&P Full Series

short	long	band	n.buys.	n.sells.	meanbuy	buyt	meansell	sellt	avret	tstat
S&P Full Series										
1	50	0	14217	9172	0.0402844	5.471	0.0094225	0.614	0.0497069	3.756
1	50	0.001	13989	8955	0.0400977	5.395	0.0060858	0.390	0.0461835	3.532
1	150	0	15053	8236	0.040253	5.548	0.0159412	0.958	0.0561942	4.208
1	150	0.001	14933	8141	0.0393915	5.405	0.0176831	1.053	0.0570746	4.191
1	200	0	15361	7878	0.0375695	5.204	0.0140289	0.815	0.0515984	3.927
1	200	0.001	15275	7791	0.038149	5.268	0.0139899	0.806	0.0521389	3.959
1	2	0	12553	10882	0.068567	7.281	0.0347528	2.916	0.1033198	7.064
1	2	0.001	9546	8373	0.0837157	7.371	0.0424438	2.915	0.1261594	7.079
S&P Full Series: buy/sell signal generated as normal except the previous days return has to be negative/positive										
1	50	0	5720	3927	-0.007819	-0.643	-0.062844	-2.831	-0.070664	-2.614
1	50	0.001	5608	3810	-0.009305	-0.756	-0.06461	-2.840	-0.073915	-2.693
1	150	0	6388	3709	-0.012482	-1.047	-0.045821	-1.956	-0.058303	-2.161
1	150	0.001	6332	3660	-0.014356	-1.199	-0.045783	-1.933	-0.060139	-2.244
1	200	0	6625	3603	-0.008348	-0.710	-0.058791	-2.458	-0.067139	-2.300
1	200	0.001	6582	3559	-0.00794	-0.673	-0.060624	-2.509	-0.068563	-2.312
1	2	0	0	0	NaN	NaN	NaN	NaN	NaN	NaN
1	2	0.001	0	0	NaN	NaN	NaN	NaN	NaN	NaN

Table 6 - FT30 Full Series

short	long	band	n.buys.	n.sells.	meanbuy	buyt	meansell	sellt	avret	tstat
FT30 Full Series										
1	50	0	13084	9192	0.0552812	7.264	0.0389864	2.919	0.0942676	6.846
1	50	0.001	12860	8992	0.056529	7.358	0.0394392	2.904	0.0959682	6.888
1	150	0	13609	8568	0.0399866	5.534	0.0188291	1.305	0.0588157	4.466
1	150	0.001	13497	8457	0.0408888	5.632	0.0194342	1.331	0.0603231	4.544
1	200	0	13859	8268	0.0394898	5.501	0.0203343	1.372	0.059824	4.532
1	200	0.001	13763	8177	0.0401392	5.571	0.0225527	1.508	0.0626919	4.680
1	2	0	11399	10921	0.1285189	14.046	0.1006847	9.291	0.2292036	16.305
1	2	0.001	8750	7854	0.1489697	13.444	0.1329005	9.383	0.2818702	15.951
FT30 Full Series: buy/sell signal generated as normal except the previous days return has to be negative/positive										
1	50	0	5021	3807	-0.05988	-4.739	-0.116168	-6.130	-0.176047	-7.738
1	50	0.001	4912	3718	-0.061164	-4.781	-0.117359	-6.091	-0.178524	-7.737
1	150	0	5538	3800	-0.070654	-5.916	-0.137373	-6.840	-0.208028	-9.051
1	150	0.001	5488	3748	-0.070609	-5.872	-0.137191	-6.748	-0.2078	-8.953
1	200	0	5717	3719	-0.071579	-6.053	-0.130305	-6.384	-0.201884	-8.801
1	200	0.001	5675	3673	-0.069763	-5.882	-0.129067	-6.267	-0.19883	-8.599
1	2	0	0	0	NaN	NaN	NaN	NaN	NaN	NaN
1	2	0.001	0	0	NaN	NaN	NaN	NaN	NaN	NaN

Table 7 – FTSE- Full Series

short	long	band	n.buys.	n.sells.	meanbuy	buyt	meansell	sellt	avret	tstat
FTSE Full Series										
1	50	0	8684	4581	0.0713051	7.687	0.0068877	0.358	0.0781928	5.452
1	50	0.001	8573	4461	0.072309	7.725	0.0085641	0.436	0.0808731	5.538
1	150	0	9406	3759	0.0617877	6.986	-0.002406	-0.106	0.0593818	4.796
1	150	0.001	9354	3709	0.0629108	7.110	-0.003475	-0.151	0.0594355	4.843
1	200	0	9710	3405	0.057646	6.593	-0.006405	-0.261	0.0512412	4.512
1	200	0.001	9675	3373	0.0585491	6.687	-0.007427	-0.300	0.0511218	4.553
1	2	0	7621	5690	0.1130083	10.187	0.0478732	3.235	0.1608815	9.512
1	2	0.001	5337	4541	0.1373748	9.878	0.0647264	3.730	0.2021013	9.501
FTSE Full Series: buy/sell signal generated as normal except the previous days return has to be negative/positive										
1	50	0	3230	2119	-0.01392	-0.894	-0.092579	-3.504	-0.106499	-3.204
1	50	0.001	3180	2063	-0.014246	-0.906	-0.093243	-3.449	-0.107488	-3.174
1	150	0	3743	1822	-0.019307	-1.320	-0.113698	-3.706	-0.133005	-3.572
1	150	0.001	3714	1795	-0.016622	-1.134	-0.115263	-3.712	-0.131885	-3.448
1	200	0	3920	1650	-0.025968	-1.770	-0.116382	-3.431	-0.14235	-3.662
1	200	0.001	3909	1635	-0.024392	-1.664	-0.116445	-3.407	-0.140838	-3.571
1	2	0	0	0	NaN	NaN	NaN	NaN	NaN	NaN
1	2	0.001	0	0	NaN	NaN	NaN	NaN	NaN	NaN

Table 8. Descriptive statistics for daily index returns

Country (index)	Maximum	Minimum	Mean ($\times 10^{-2}$)	Standard Deviation	Skewness	Kurtosis	Auto-Correlation (lag 1)
Panel A: Developed Markets (21)							
Australia (ASXAORD)	0.0574	-0.0855	0.0187	0.0094	-0.5621	6.7115	-0.005
Austria (ATXINDX)	0.1202	-0.1025	0.0139	0.0136	-0.3852	8.0442	0.064**
Belgium (TOTMKBG)	0.0823	-0.0815	0.0233	0.0109	-0.1768	6.3159	0.092**
Canada (TTOCOMP)	0.0937	-0.0979	0.0235	0.0107	-0.7327	10.1913	0.006
Denmark (COSEASH)	0.0820	-0.1058	0.0373	0.0107	-0.4328	6.4436	0.066**
Finland (TOTMKFN)	0.1534	-0.1824	0.0273	0.0188	-0.3761	7.3840	0.013
France (FRCACAT)	0.1022	-0.0926	0.0187	0.0131	-0.0779	5.3904	0.000
Germany (TOTLIBD)	0.1946	-0.0940	0.0227	0.0126	0.3822	14.6704	0.019
Hong Kong (HNGKNGI)	0.1724	-0.1473	0.0169	0.0163	0.0914	10.6205	-0.004
Ireland (TOTLIIR)	0.0715	-0.1200	0.0238	0.0123	-0.8695	8.3359	0.031**
Italy (TOTMKIT)	0.1048	-0.0864	0.0093	0.0135	-0.1293	4.3515	0.005
Japan (TOKYOSE)	0.1286	-0.1001	-0.0035	0.0132	-0.2858	6.2123	0.027
Netherlands (TOTMKNL)	0.0930	-0.0922	0.0171	0.0126	-0.3046	6.0292	0.027**
New Zealand (TOTMKNZ)	0.0915	-0.1279	0.0112	0.0074	-0.9755	25.2967	0.016
Portugal (TOTMKPT)	0.0950	-0.1056	0.0079	0.0107	-0.3426	8.7261	0.094**
Singapore (TOTLISG)	0.0849	-0.0887	0.0077	0.0116	-0.1964	5.3563	0.018**
Spain (MADRIDI)	0.1374	-0.0968	0.0252	0.0137	0.0028	6.0180	0.029**
Sweden (SWEDOMX)	0.1102	-0.0853	0.0312	0.0149	0.0812	3.9787	-0.011
Switzerland (TOTMKSW)	0.0981	-0.0726	0.0246	0.0106	-0.2336	6.1603	0.048**
UK (TOTMKUK)	0.0886	-0.0871	0.0171	0.0110	-0.2283	6.4732	-0.005
USA (TOTMKUS)	0.1090	-0.0941	0.0295	0.0120	-0.2748	8.2607	-0.051**
Panel B: Developed Markets (18)							
Brazil (TOTMKBR)	0.1952	-0.1055	0.0373	0.0158	0.1288	10.7526	0.067**
Chile (TOTMKCL)	0.0941	-0.0603	0.0201	0.0087	0.1203	7.7624	0.215**
China (CHSCOMP)	0.2699	-0.1791	0.0210	0.0177	0.3574	17.5153	-0.003

Greece (GRAGENL)	0.1343	-0.1021	0.0035	0.0176	-0.0380	3.8554	0.105**
India (TOTMKIN)	0.1508	-0.1259	0.0364	0.0152	-0.3224	7.0537	0.094**
Indonesia (JAKCOMP)	0.1312	-0.1273	0.0447	0.0156	-0.2077	8.4719	0.145**
Israel (TOTMKIS)	0.0753	-0.0998	0.0274	0.0119	-0.3140	4.3463	0.029**
Malaysia (FBMKLCI)	0.2082	-0.2415	0.0095	0.0132	0.5017	58.8091	0.056**
Mexico (MXIPC35)	0.1215	-0.1431	0.0538	0.0151	0.0646	7.0022	0.092**
Pakistan (PKSE100)	0.1276	-0.1321	0.0493	0.0153	-0.3605	6.4973	0.084**
Philippines (PSECOMP)	0.1618	-0.1309	0.0175	0.0141	0.1993	11.5559	0.152**
Russia (TOTLIRS)	0.2933	-0.2041	0.0776	0.0266	0.2640	14.2359	0.023
South Africa (JSEOVER)	0.0742	-0.1269	0.0461	0.0122	-0.4845	6.7224	0.065**
South Korea (KORCOMP)	0.1128	-0.1280	0.0123	0.0178	-0.2003	5.3253	0.055**
Sri Lanka (TOTMKCY)	0.1990	-0.1667	0.0312	0.0113	-0.0273	38.2347	0.200**
Taiwan (TAIWGHT)	0.0852	-0.0994	0.0043	0.0145	-0.1977	3.2559	0.025
Thailand (TOTMKTH)	0.1212	-0.1780	0.0058	0.01749	0.1924	7.9681	0.073**
Turkey (TOTMKTK)	0.1703	-0.1946	0.1097	0.0246	0.0071	5.7214	0.018

The table shows descriptive statistics for daily returns of world stock market indices for the period 1994 to 2014. The descriptive statistics for developed markets are reported in Panel A and those for developing markets in Panel B. ** Significant at 5%

Table 9: The performance of MA rules in developed markets. ***, **, * indicates significance at 1%, 5% and 10% respectively.

	short	long	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
AUSTRAL	1	50	3286	1882	0.029676	-0.003842	0.52	0.5	0.025834
	1	100	3387	1681	0.024636	0.007650	0.52	0.5	0.016986
	1	200	3653	1365	0.024143	-0.005961	0.52	0.49	0.018183
AUSTRIA	1	50	3082	2086	0.069783	-0.067283**	0.51	0.48	0.137065***
	1	100	3083	1985	0.067944	-0.063624**	0.51	0.48	0.131567***
	1	200	3114	1904	0.031308	-0.010793	0.5	0.49	0.042101
BEL	1	50	3298	1870	0.043584	-0.012028	0.53	0.51	0.055612
	1	100	3368	1700	0.050597	-0.029191	0.53	0.5	0.079788**
	1	200	3472	1546	0.055177	-0.046348**	0.54	0.48	0.101524**
CAN	1	50	3316	1852	0.049926	-0.018791	0.54	0.5	0.068717*
	1	100	3392	1676	0.043322	-0.012922	0.53	0.51	0.056245
	1	200	3575	1443	0.036896	-0.009077	0.53	0.51	0.045972
FIN	1	50	3079	2089	0.075009	-0.042008	0.52	0.48	0.117016**
	1	100	3207	1861	0.067844	-0.037579	0.52	0.48	0.105423
	1	200	3218	1800	0.036285	0.007203	0.52	0.49	0.029082
FRA	1	50	3244	1924	0.030053	-0.000990	0.51	0.51	0.031043
	1	100	3271	1797	0.043738	-0.025370	0.52	0.5	0.069108
	1	200	3339	1679	0.038819	-0.018606	0.52	0.49	0.057425
GER	1	50	3279	1889	0.051068	-0.024430	0.54	0.5	0.075497*
	1	100	3238	1830	0.047801	-0.018672	0.54	0.51	0.066473
	1	200	3522	1496	0.037099	-0.009948	0.54	0.49	0.047047
HK	1	50	3007	2161	0.060409	-0.035718	0.5	0.47	0.096126*
	1	100	3013	2055	0.063697	-0.044008	0.5	0.48	0.107705**
	1	200	3218	1800	0.037432	-0.017236	0.49	0.48	0.054668
IRE	1	50	3216	1952	0.062772	-0.036643*	0.52	0.49	0.099415**
	1	100	3293	1775	0.049977	-0.020378	0.52	0.5	0.070355*
	1	200	3514	1504	0.053858	-0.045415*	0.52	0.48	0.099273**
ITA	1	50	2966	2202	0.035009	-0.021509	0.51	0.5	0.056517
	1	100	2935	2133	0.032616	-0.020110	0.51	0.49	0.052725*
	1	200	3016	2002	0.038189	-0.029532	0.52	0.49	0.067721*

Table 10: The performance of MA rules in developed markets. ***, **, * indicates significance at 1%, 5% and 10% respectively.

	short	long	n.Buys	n.Sells	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
JAP	1	50	2580	2588	0.039060	-0.044234	0.50	0.45	0.083293**
	1	100	2534	2534	0.036718	-0.036953	0.50	0.46	0.073672**
	1	200	2417	2601	0.030132	-0.025314	0.50	0.46	0.055446
NETH	1	50	3272	1896	0.043097	-0.027481	0.53	0.50	0.070577*
	1	100	3324	1744	0.049107	-0.043310	0.53	0.50	0.092417**
	1	200	3463	1555	0.039552	-0.034156	0.54	0.48	0.073708
NZ	1	50	3006	2162	0.028803	-0.009220	0.51	0.5	0.038023*
	1	100	3028	2040	0.022993	-0.007458	0.51	0.5	0.030451
	1	200	3261	1757	0.012569	0.009454	0.50	0.51	0.003114
PORT	1	50	2865	2303	0.070643**	-0.070805***	0.52	0.48	0.141448***
	1	100	2793	2275	0.068152**	-0.063757***	0.52	0.48	0.131910***
	1	200	2834	2184	0.065416**	-0.063061***	0.54	0.47	0.128476***
SING	1	50	2919	2249	0.046890	-0.036933	0.53	0.49	0.083823**
	1	100	2918	2150	0.050806	-0.042783*	0.53	0.48	0.093589***
	1	200	2900	2118	0.042120	-0.031709	0.53	0.48	0.073829**
SPA	1	50	3126	2042	0.044879	-0.005552	0.52	0.51	0.050432
	1	100	3255	1813	0.047984	-0.010932	0.52	0.51	0.058916
	1	200	3214	1804	0.050166	-0.016240	0.53	0.50	0.066406
SWE	1	50	3303	1865	0.048511	-0.000650	0.52	0.49	0.049161*
	1	100	3356	1712	0.059800	-0.027460	0.52	0.48	0.087260
	1	200	3513	1505	0.047757	-0.015533	0.52	0.47	0.063290
SWIT	1	50	3370	1798	0.041929	-0.008517	0.52	0.51	0.050446
	1	100	3434	1634	0.043014	-0.013107	0.53	0.5	0.056121
	1	200	3407	1611	0.045901	-0.024023	0.53	0.49	0.069924
UK	1	50	3254	1914	0.017491	0.017060	0.51	0.53	0.000431
	1	100	3325	1743	0.018366	0.013440	0.52	0.51	0.004926
	1	200	3489	1529	0.017062	0.012880	0.52	0.51	0.004181
US	1	50	3419	1749	0.026051	0.039857	0.53	0.52	-0.013806
	1	100	3490	1578	0.034815	0.014343	0.53	0.50	0.020472
	1	200	3598	1420	0.039092	-0.003166	0.53	0.49	0.042259

Table 11: The performance of the MA rules in Developing Markets. ***, **, * indicates significance at 1%, 5% and 10% respectively.

	short	long	n.Buys	n.Sells	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
BRA	1	50	3171	1997	0.085647	-0.034919	0.51	0.48	0.120566**
	1	100	3276	1792	0.078997	-0.022367	0.51	0.48	0.101364**
	1	200	3374	1644	0.056693	0.014957	0.51	0.49	0.041736
CHIL	1	50	2953	2215	0.068193**	-0.045929***	0.53	0.45	0.114122***
	1	100	2993	2075	0.054464*	-0.028931**	0.52	0.46	0.083396***
	1	200	2781	2237	0.046124	-0.016185	0.52	0.47	0.062309***
CHIN	1	50	2635	2533	0.093899*	-0.046335*	0.53	0.44	0.140234***
	1	100	2632	2436	0.077552	-0.025638	0.51	0.46	0.103190**
	1	200	2582	2436	0.075329	-0.026064	0.51	0.46	0.101394**
GRE	1	50	2635	2533	0.108845**	-0.106876***	0.52	0.45	0.215720***
	1	100	2616	2452	0.114895***	-0.113616***	0.52	0.45	0.228510***
	1	200	2615	2403	0.085399*	-0.088501**	0.52	0.45	0.173900***
INDIA	1	50	3021	2147	0.125271**	-0.084263***	0.53	0.47	0.209534***
	1	100	2951	2117	0.111112*	-0.051754**	0.53	0.48	0.162867***
	1	200	3086	1932	0.076066	-0.007166	0.53	0.48	0.083232*
INDON	1	50	3167	2001	0.132913**	-0.089898***	0.52	0.48	0.222812***
	1	100	3234	1834	0.098021	-0.036024**	0.51	0.49	0.134045***
	1	200	3441	1577	0.074868	-0.015564	0.52	0.48	0.090432
ISRA	1	50	3118	2050	0.060292	-0.016458	0.50	0.48	0.076750**
	1	100	3144	1924	0.061104	-0.022127*	0.50	0.48	0.083231**
	1	200	3136	1882	0.053351	-0.013226	0.50	0.48	0.066577*
MAL	1	50	3032	2136	0.070379*	-0.067562**	0.51	0.46	0.137941***
	1	100	3035	2033	0.061985	-0.059457**	0.51	0.46	0.121442***
	1	200	3384	1634	0.048861	-0.066377**	0.52	0.44	0.115238**
MEX	1	50	3301	1867	0.087266	0.000506	0.52	0.50	0.086760
	1	100	3384	1684	0.077925	0.028707	0.52	0.49	0.049218
	1	200	3585	1433	0.067066	0.036658	0.52	0.48	0.030409*
PAK	1	50	3121	2047	0.124989**	-0.061132***	0.53	0.45	0.186121***
	1	100	3225	1843	0.094520	-0.006944	0.52	0.46	0.101463**
	1	200	3499	1519	0.099078	-0.036311**	0.52	0.44	0.135389**
PHIL	1	50	2966	2202	0.087623**	-0.072221**	0.49	0.46	0.159844***
	1	100	3066	2002	0.085338**	-0.076700**	0.49	0.46	0.162038***
	1	200	3165	1853	0.047464	-0.030138	0.49	0.46	0.077602*
SK	1	50	2808	2360	0.076549	-0.063503*	0.51	0.48	0.140053***
	1	100	2961	2107	0.056654	-0.040920	0.51	0.48	0.097574*
	1	200	2878	2140	0.061442	-0.045620	0.51	0.48	0.107063*
SL	1	50	2835	2333	0.126026***	-0.079192***	0.52	0.42	0.205218***
	1	100	2814	2254	0.103847**	-0.037331***	0.50	0.45	0.141178***
	1	200	2686	2332	0.096345**	-0.023474**	0.51	0.45	0.119818***
TAI	1	50	2855	2313	0.066446*	-0.069899**	0.50	0.46	0.136345***
	1	100	2915	2153	0.047712	-0.045144	0.50	0.46	0.092856**
	1	200	2980	2038	0.03183	-0.022364	0.50	0.46	0.054194
THA	1	50	2802	2366	0.077046*	-0.074671*	0.48	0.45	0.151717***
	1	100	2923	2145	0.033706	-0.026447	0.48	0.45	0.060154*
	1	200	2962	2056	0.029005	-0.029030	0.48	0.45	0.058035
TUR	1	50	3117	2051	0.144921	0.047856	0.51	0.50	0.097065
	1	100	3256	1812	0.141203	0.027193	0.51	0.50	0.114010
	1	200	3425	1593	0.131648	0.033810	0.51	0.49	0.097837

Table 12: The Performance of rule where buy/sell return is followed by buy/sell return***, **, * indicates significance at 1%, 5% and 10% respectively. †indicates avret greater than return from MA(1,50,0) for same country.

	n.buys.	n.sells.	buy	sell	avret
Australia	2766	2443	0.0002942	5.94E-05	0.0002348
Austria	2756	2455	0.0008469	-0.0006535	0.0015003***†
Belgium	2724	2492	0.0008587	-0.000446	0.0013047***†
Canada	2913	2303	0.0008474	-0.000535	0.0013825***†
Denmark	2580	2310	0.0009462	-0.0002682	0.0012143***†
Finland	2716	2498	0.000903	-0.0004116	0.0013146**†
France	2763	2452	0.0003042	5.83E-05	0.0002459
Germany	2835	2378	0.0007718	-0.0004154	0.0011872***†
HK	2552	2661	0.0005676	-0.000209	0.0007766*
Ireland	2789	2426	0.0007314	-0.0003266	0.001058**†
Italy	2741	2474	0.0002602	-9.473E-05	0.0003549
Japan	2496	2714	0.0003111	-0.0003483	0.0006594*
Netherlands	2718	2498	0.0005341	-0.0002202	0.0007543**†
New Zealand	2828	2386	0.0005033	-0.0003472	0.0008504***†
Portugal	2771	2437	0.0011063	-0.0011047	0.002211***†
Singapore	2760	2456	0.0003921	-0.0002749	0.000667**
Spain	2862	2351	0.0006169	-0.0001852	0.0008021**†
Sweden	2658	2555	0.0004993	0.000131	0.0003687
Switzerland	2796	2417	0.00054	-9.366E-05	0.0006336†
UK	2729	2484	0.0002305	0.00011	0.0001208†
US	2778	2437	0.0001112	0.000508	-0.000397
Brazil	2730	2486	0.0014063	-0.0007556	0.0021619***†
Chile	2659	2555	0.0017779	-0.0014474	0.0032252***†
China	2678	2536	0.0004039	-5.846E-07	0.0004045
Greece	2773	2444	0.0019781	-0.0021692	0.0041473***†

India	2818	2395	0.0018207	-0.0013475	0.0031682***†
Indonesia	2792	2421	0.0023122	-0.0017462	0.0040584***†
Israel	2823	2389	0.0006501	-0.0001552	0.0008053***†
Malaysia	2834	2382	0.0013123	-0.0013615	0.0026738***†
Mexico	2731	2485	0.0018289	-0.0008834	0.0027123***†
Pakistan	2600	2609	0.0020399	-0.0010192	0.003059***†
Philippines	2522	2691	0.002146	-0.0016779	0.0038239***†
Russia	2283	2061	0.0011912	0.000316	0.0008753
SA	2588	2434	0.0011951	-0.00032	0.0015151***†
SK	2755	2461	0.0007435	-0.0005779	0.0013214***
SL	2678	2531	0.0022112	-0.0016652	0.0038764***†
Taiwan	2763	2447	0.0004857	-0.0004626	0.0009482***
Thailand	2432	2784	0.001183	-0.0009271	0.00211***†
Turkey	2639	2578	0.0016303	0.000551	0.0010797†

Table 13: Moving Average Rules (1,50,0) – Normal Rule where a buy/sell signal is generated in the normal way except the previous days return has to be negative/positive***, **, * indicates significance at 1%, 5% and 10% respectively. ‡ indicates an avret sign opposite to normal MA(1,50,0) rule.

	n.buys.	n.sells.	meanbuy	meansell	avret
Australia	1318	782	0.0003787	0.000633	-0.000254***‡
Austria	1318	782	0.0003787	0.000633	-0.000254***‡
Belgium	1302	788	3.77E-05	0.001557	-0.00152**‡
Canada	1267	789	1.188E-05	0.000877	-0.000866‡
Denmark	1229	660	3.461E-05	0.000365	-0.00033‡
Finland	1212	864	0.0005535	0.00087	-0.000317**‡
France	1315	814	0.0001827	0.000136	4.671E-05
Germany	1277	809	0.0002864	0.001128	-0.000842‡
HK	1221	875	7.583E-05	0.000315	-0.000239‡
Ireland	1303	814	9.945E-05	0.000197	-9.77E-05**‡
Italy	1213	937	0.0002229	4.868E-05	0.0002716
Japan	979	1015	-3.58E-05	9.33E-05	-0.000129‡
Netherlands	1289	786	-3.67E-05	0.000238	-0.000275‡
New Zealand	1176	913	-0.000333	0.000359	-0.000691**‡
Portugal	1121	969	-0.000294	0.000811	-0.001105**‡
Singapore	1140	927	0.0003272	0.000196	0.0001311
Spain	1189	857	-0.00028	-0.0001261	-0.000154‡
Sweden	1297	751	0.0004523	0.000598	-0.000145‡
Switzerland	1316	754	0.0001996	0.000701	-0.000501‡
UK	1338	821	2.505E-05	0.000312	-0.000287‡
US	1337	736	0.0003164	-0.0002505	0.0005668‡
Brazil	1227	807	-7.47E-05	0.001679	-0.001753**‡
Chile	1171	889	-0.00066	0.002166	-0.002826***‡
China	961	1003	0.0005682	0.00011	0.0004587

Greece	1034	1003	-0.001488	0.001177	-0.002665***‡
India	1175	895	-0.000401	0.001379	-0.00178***‡
Indonesia	1200	847	-0.000485	0.00254	-0.003025***‡
Israel	1205	828	0.0001123	0.000269	-0.000156‡
Malaysia	1180	862	-0.00022	0.001663	-0.001883***‡
Mexico	1313	782	-0.000416	0.002283	-0.002699***‡
Pakistan	1129	809	5.441E-06	0.002014	-0.002009***‡
Philippines	1189	879	-0.000942	0.002466	-0.003408***‡
Russia	1043	733	0.0010492	0.00116	-0.000111‡
SA	1307	660	-0.000216	0.001463	-0.001679**‡
SK	1069	981	0.0003919	0.000616	-0.000224‡
SL	1062	897	-0.000802	0.001768	-0.00257***‡
Taiwan	1105	933	0.0001554	-0.0003992	0.0005546
Thailand	1140	927	-0.000222	0.001219	-0.001441*‡
Turkey	1373	864	0.0002939	8.58E-05	0.0002081