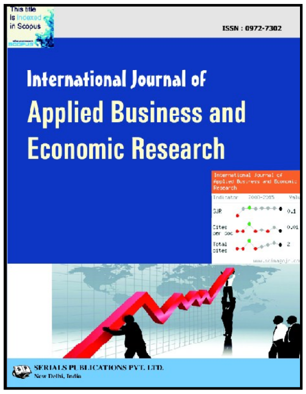

International Journal of Applied Business and Economic Research

ISSN : 0972-7302

available at http: www.serialsjournal.com

Volume 15 • Number 20 • 2017

Asymmetry between Uptrend and Downtrend Identification: a Tale of Moving Average Trading Strategy

Carlin CHU Chun-fai[1]

[1]*Assistant Professor, Math and Statistics team, School of Science and Technology, The Open University of Hong Kong, Hong Kong.*
E-mail: ccfchu@ouhk.edu.hk

Abstract: Most market participants are risk adverse and people tend to close their long positions once they perceive a formation of downturn in the market. Large sudden price drops can always be observed near the end of uptrends. On the other hand, people tend to have their own preferences in deciding the market entrance timings and large sudden price changes are relatively less commonly observed near the end of downtrends. Typical Moving Average strategies employ the same approach, using a single pair of time series, to locate the ending points of uptrends and downtrends. This approach does not consider the asymmetry of price changes near the end of uptrend and downtrend distinctively. To cater for the differences, a new approach using distinct pairs of time series for locating uptrends and downtrends is proposed.

Performance of the proposed strategy is evaluated using stock market index series from 8 different developed countries including US, UK, Australia, Germany, Canada, Japan, Hong Kong and Singapore under 3 moving average calculation methods. The empirical results indicate that the proposed strategy outperforms the typical strategy and the buy-and-hold strategy. Recommended heuristics for selecting an appropriate MA length will also be addressed in this study.

Keywords: Technical trading, moving average, financial markets, trend identification, asymmetrical information.

1. INTRODUCTION

1.1. Background

Effective identification of market uptrend and downtrend is one of the crucial topics in financial trading area. One of the most prevalent methodologies for trend identification is Moving Average (MA) strategy which makes use of averaged historical prices series to locate the beginning and ending time points of a trend. The beginning of an uptrend is identified by an occurrence of a buy-signal and the ending is marked by a sell-signal, and vice versa. Buy-signals and sell-signals are generated according to the crossover directions between a pair of time series. The strategy recommends long positions for identified uptrend spans and short positions for downtrend spans.

Typical MA strategy generates the buy-signals and sell-signals with a single pair of time series, using the same approach to locate the ending points of uptrends and downtrends. This approach does not consider investor's preference towards risk. Most market participants are risk averse and they would like to avoid potential losses, closing long positions once they perceive a formation of market downtrend. As a result, the exit timings from different market participants tend to be similar to each other and the resultant price drops would be exaggerated due to a large amount of closings in a short time interval. A large sudden price drop can always be observed at the end of an uptrend (beginning of a downtrend).

On the other hand, price changes observed near the end of downtrends (beginning of uptrends) are relatively less prominent. Various types of investors exist in the market, some are aggressive and some are conservative, and there is not any 'majority' agreed principle to select the best timing to enter into the market. Participants engage in long positions in various time points and the magnitude of price changes at the beginning of an uptrend (end of downtrend) is not as prominent as the one observed at the end of an uptrend.

Due to the difference of magnitude of price changes observed at the end of uptrends and downtrends, a new approach is proposed to locate their ending time points distinctively. Furthermore, we speculate that the use of a more responsive time series (*i.e.* with shorter MA lengths) to locate the ending time points of uptrends would most probably improve the quality of Long positions suggested by the trading strategy.

1.2. Problems and Objectives

This paper aims to demonstrate the difference of the characteristics of price changes in uptrend and downtrend spans, and propose a new strategy catering for the difference. The following 3 research questions will be addressed.

1. Study whether there is an information asymmetry between uptrends and downtrends. In other words, determine whether there is a significant difference between the price changes observed in uptrends and those observed in downtrends.
2. Explore whether the use of different lengths to locate the ending time points helps improving the quality of suggested Long positions and Short positions respectively under various settings.
3. Compare the best results achieved by the asymmetric and symmetric approaches in terms of the overall average return from both Long and Short periods.

A short review on the applications of Moving Average trading strategy and usages of asymmetric market information in financial time series volatility modeling will be stated in Section 2. The methodology of our proposed trading strategy which is capable to tackle the asymmetry between uptrend and downtrend will be introduced in Section 3. The empirical results will be discussed in Section 4 and the conclusions will be addressed in the final section.

2. STUDY REFERENCES

Moving Average (MA) trading strategy is a prevalent methodology for identifying uptrends and downtrends of the prices of financial assets. It makes use of averaged historical prices series to locate the beginning and ending time points of a trend. One of the most famous works on MA strategy is Brock, Lakonishok and LeBaron (1992) paper. They investigated the performance of a group of strategies on Dow Jones Index and showed strong support of the worthiness of MA strategy with the use of the bootstrap technique. Levich and Thomas (1991) studied the effectiveness of applications in the foreign exchange markets and showed significant profitability can be achieved by their strategy. Lots of works has been done on the applications of MA strategy, such as Gunasekarage and Power (2001) carried out their investigation using index data from four emerging South Asian capital markets; Fong and Yong (2005) applied over 800 MA rules on 30 internet stock prices; and Lai and Lau (2006) conducted a study on nine popular Asian market indexes[1]. Apart from the applications on daily price series, MA trading strategy has also been employed in high frequency trading. Marshall *et al.* (2008) and Zhou *et al.* (2015) employed MA strategies in a high frequency trading system respectively. Furthermore, MA strategies have been treated as viable input components of machine-learning financial trading systems[2].

Risk aversion is commonly observed in the financial market as people always try to avoid loss. People tend to close their long positions immediately once they perceive a downturn in the market. Market participants react differently to positive news and negative news and it is well agreed that days with negative returns always have a bigger impact on the volatilities on the following days. The larger impact given by negative returns is considered as the "leverage effect" and it has been well explored in the financial time series volatility modeling literature. Several models including AGARCH, EGARCH, GJR-GARCH, NAGARCH and APGARCH were developed for catering the asymmetrical impact from positive and negative returns[3].

The asymmetrical impact created by negative and positive returns has been noted for a long time in the volatility modelling literature but the consideration of the impact on trading strategy is very limited. All of the works on MA trading strategy mentioned before did not consider the asymmetry between price changes near the end of uptrend and downtrend distinctively. This work aims to explore the potentials of utilizing the asymmetric information content to develop a more profitable trading strategy.

3. METHODOLOGY AND DATA

3.1 Research Methodology

Risk averseness is commonly observed in most market participants. People in long positions tend to close their position once they perceive a formulation of downtrend. As a result, the exit timings from all participants tend to be similar to each other and the resultant price drops would be exaggerated due to a large amount of closings in a short time interval. Large sudden price drops can always be observed near the end of uptrends. On the other hand, people tend to have their own preferences in entering the market and therefore large sudden price changes are relatively less commonly observed near the end of downtrends.

Typical MA trading strategies make use of a single pair of time series, asset price series and a moving average price series, to identify trends. The strategies recommend Long positions for identified uptrend spans and Short positions for downtrend spans. Trends are identified by buy-signals and sell-signals which are generated as a result of the crossover points between the two time series. A crossover point appears when the price of an asset changes (crossovers) from one side of the moving average series to another side.

A buy-signal is generated when the asset price changes from below the moving average value to above the value in two consecutive days (*i.e.* price below the MA value on day t and price above the MA value on day $t+1$). A sell-signal is generated when the price changes downwards, causing a downward crossover between the two series. An uptrend is identified by an occurrence of a buy-signal and ended with an occurrence of a sell-signal, and vice versa.

The responsiveness (sensitivity) of MA trading strategy is adjusted through a MA length parameter. The length controls the number of historical days and the weighting on each price value in the construction of a moving average time series. There are several formulas for constructing a moving average series but the length parameter plays the same role in most settings. A longer length represents the inclusion of more distant prices in the calculation process and, as a result, the constructed series will be less responsive (sensitive) to the latest changes. A shorter length places heavier weights on recent changes and therefore it is a more responsive to the current market condition.

The approach used by typical MA trading strategies does not consider the asymmetry of price changes near the end of uptrends and downtrends distinctively. To cater for the difference, a new approach is proposed. Two separate pairs of time series are proposed for identifying uptrends and downtrends separately and a short MA length is recommended to model the sell-signals for locating the ending time points of uptrends. The proposed method is named as 'Asymmetric approach' and the typical method which makes use of a single pair of time series is regarded as 'Symmetric approach' for the rest of this study.

The empirical analysis will be carried out with the use of 3 moving average formulas and 7 market index series. The 3 MA formulas are Simple Moving Average, Exponential Moving Average and Triangular Moving Average. The 7 market indexes includes S&P 500, FTSE 100, Nikkei 225, Deutscher Aktienindex, TSX Composite index, ASX 200 and Hang Seng Index.

3.2. Symmetric and Asymmetric Approach

Typical Moving Average trading strategies make use of a single pair of time series to generate buy-signals and sell-signals. There are different ways to generate the signals and this paper considers a fundamental setting which is described as:

1. Buy-signals are generated when the current price crossovers the MA line from below OR current price equals to the MA line. (*i.e.* $P_t \geq S_t(n)$).
2. Sell-signals are generated when the current price crossovers the MA line from above. (*i.e.* $P_t < S_t(n)$).
3. Long positions are identified as days after receiving a buy-signal to the day (inclusive) of receiving a sell-signal.
4. Short positions are considered as days after receiving a sell-signal to the day (inclusive) of receiving a buy-signal.

The P_t denotes the closing price on day t and $S_t(n)$ denotes the value of the moving average series on day t based on the MA length n. The following 3 MA formulas will be used to compute the $S_t(n)$ series.

– Simple Moving Average (SMA):

$$SMA_t(n) = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i} \quad \text{(Eqt. 1)}$$

– Exponential Moving Average (EMA):

$$EMA_t(n) = P_t \times k + EMA_{t-1}(n) \times (1-k) \quad \text{(Eqt. 2)}$$

where $k = \frac{2}{n-1}$ which is the smoothing constant for calculating the EMA series.

– Triangular Moving Average (TMA):

$$TMA_t(n) = \frac{1}{n}\sum_{i=0}^{n-1} SMA_{t-i}(n) \quad \text{(Eqt. 3)}$$

Our proposed asymmetric trading strategy aims to explore the potentials from the information asymmetry observed in uptrend and downtrend. The single MA length n can be redefined into two lengths (length pair), one for buy-signal and the other for sell-signal. Besides, the length pairs for Long and Short position identifications are different. A Long position is identified by using length p_L for generating buy-signal and length q_L for sell-signal while the Short position is found by another pair of lengths. The modifications can be summarized as:

1. Long positions are identified through buy-signals generated by length p_L and sell-signal generated by length q_L.
2. Short positions are identified through sell-signals generated by length q_S and buy-signal generated by length p_S.

The spans of Long position are identified by pairs of buy-signals and sell-signals. Every span of long position begins with a buy-signal and ends with the first following sell-signal. The second (and the rest of) following sell-signal is ignored. Short position is identified using the same logic, beginning with a sell-signal and ending with the first following buy-signal. The rest of the following buy-signals are ignored. In other words, for identifying Long positions, the corresponding buy-signals and sell-signals are generated by $S_t(p_L)$ and $S_t(q_L)$ respectively. Another pair of series $S_t(p_s)$ and $S_t(q_s)$ are used to identify Short positions.

The potential improvements of the proposed approach are investigated in two aspects, including a) the effectiveness of using different lengths to recommend Long positions and Short positions; b) the overall performance gain (summing up the returns from Long and Short periods) from the Asymmetric approach over the Symmetric approach.

3.3. Data

The empirical study is carried out with the use of 7 different market indexes which are publicly available from Yahoo Finance. Table 1 lists out the 7 stock market indexes, their corresponding countries/cities, abbreviations and the investigation periods. The begin dates of the investigation periods are chosen according to the maximum (most distant) data available from Yahoo Finance website.

Table 1
Seven stock market indexes

Market Index	*Country/City*	*Abbreviation*	*Begin date*	*End date*
S&P 500	US	S&P500	1/3/1966	11/1/2016
FTSE 100	UK	FTSE	1/3/1984	11/1/2016
Nikkei 225	Japan	N225	1/4/1984	11/1/2016
Deutscher Aktienindex	Germany	DAX	11/26/1990	11/1/2016
S&P/TSX Composite index	Canada	TSX	6/29/1979	11/1/2016
S&P/ASX 200	Australia	ASX	11/23/1992	11/1/2016
Hang Seng Index	Hong Kong	HSI	12/31/1986	11/1/2016

4. RESULT AND DISCUSSION

4.1. Information Asymmetry between Uptrend and Downtrend

The proposition of the use two different MA length pairs for identifying uptrends and downtrends are originated from the assumption of risk averseness of market participants. People tend to react more vigorously near the end of uptrends than the end of downtrends. However, there are not any consistent guidelines in the literature to define the spans of uptrend/downtrend and therefore it is not possible to directly compare the information content between uptrends and downtrends correspondingly. An indirect support for the proposition of using distinct length pairs is considered.

The existence of difference between the price changes of days with positive returns and the changes of days with negative returns is suggested as the indirect support for the use of the Asymmetric approach. The set of days with positive returns is considered as a proxy of uptrend while the set of days with negative returns is a proxy of downtrend. It is reasonable to consider that separate ways should be used for modeling uptrend and downtrend if the properties of their proxies are significantly different to the other. The number of days, mean absolute price change and the result of Welch's t-test (one-tailed two-sample unequal variances t-test) are tabulated in Table 2.

Table 2
Properties of Price changes in days with positive and negative returns

	S&P500	*FTSE*	*N225*	*DAX*	*TSX*	*ASX*	*HSI*
Total no. of days	12762	8280	8057	6548	9354	6043	7360
Days with +ve returns	6713	4350	4162	3491	5043	3177	3818
Days with -ve returns	6048	3929	3894	3056	4310	2865	3541
Mean abs(price change) with +ve returns	4.810	33.127	157.81	51.293	46.988	26.308	142.62
Mean abs(price change) with –ve returns	5.005	35.170	166.74	55.623	51.924	27.834	147.97
p-value(Welch's t-test)	0.0881^{*}	$0.0082^{\dagger}$	$0.0120^{\dagger}$	$0.0019^{\dagger}$	$0.0004^{\dagger}$	$0.0255^{\dagger}$	0.1032

† and * indicate that the result is significance at 5% and 10% significance level respectively.

The patterns observed among the 7 market indexes look almost the same. The number of days with negative returns is fewer than the number of days with positive returns. The mean absolute price change in days with negative returns is larger than the value obtained from days with positive returns. The one-tailed Welch's test is used to test whether the mean values of absolute price change on days with negative returns is larger than the one on positive return days. 5 out of 7 indexes are significant at 5% level and 1 index is significant at 10% level. The largest p-value (HSI data set) is 0.1032 and it still shows a strong support to the asymmetry of absolute price change.

The existence of information asymmetry reinforces the feasibility of using different MA length pairs for identifying uptrends and downtrends. The actual benefits of the proposed Asymmetric approach will be discussed in the coming subsection.

4.2. Performance of Various MA Lengths for Locating Ending Time Points

The effect of using different lengths to locate the ending time points of uptrends and downtrends are discussed in this subsection. Average daily return obtained by the Long positions and Short positions which are suggested by a trading strategy is used as the performance measurement. Daily return is calculated as $\ln(P_t) - \ln(P_{t-1})$. To facilitate a concise discussion, the empirical results of S&P 500 data set on Exponential MA trading strategy are selected as the illustration. Similar findings are observed in other data sets and MA formulas[4].

To illustrate the effect of using various MA lengths for locating the ending time points of uptrends, we fix the MA length for generating buy-signals (p_L) (and adjust the length for generating sell-signal (q_L) iteratively. The average return of Long positions identified by strategies using q_L from 5 to 200 pairing with 4 fixed values of p_L are computed. The results are depicted in Figure 1.

There are four sub-plots in Figure 1 and each plot represents the average return achieved by a fixed p_L and varying q_L. The four plots depict the performance of fixed buy-signal length of 60, 90, 120 and 150 respectively. The highlighted area on the left side shows the performance of using a shorter length to locate the ending time points (*i.e.* $q_L < p_L$). The performance of the typical symmetric approach can be found on the boundary of highlighted area where $p_L = q_L$.

It is observed that shorter lengths for locating the ending time points are always more preferable than longer lengths in all four settings. A short length for generating sell-signals (*i.e.* q_S = 5 to 7) always gives the best performance under various settings for generating buy-signals, in additional to the illustrated lengths of 60, 90, 120 and 150. Preference to shorter lengths for generating sell-signals is also observed in other data sets and different MA trading strategies as well[5]. The empirical results support our speculation that a more responsive way (*i.e.* small q_L) should be used to locate the ending time points of uptrends.

The performances on Short positions are shown in Figure 2. A consistent pattern among different values of q_S cannot be observed. The diversity of principles for determining market entering timing helps to explain the variation obtained in graphs of Short positions. Neither long nor short MA lengths always outperform the other and the patterns from using different values of vary greatly q_S. Studies using other data sets and trading strategies also show a similar finding.

Apart from showing the different patterns observed in Long and Short positions, the upper bounds of the average return achieved by the Asymmetric approach under various MA lengths are plotted in

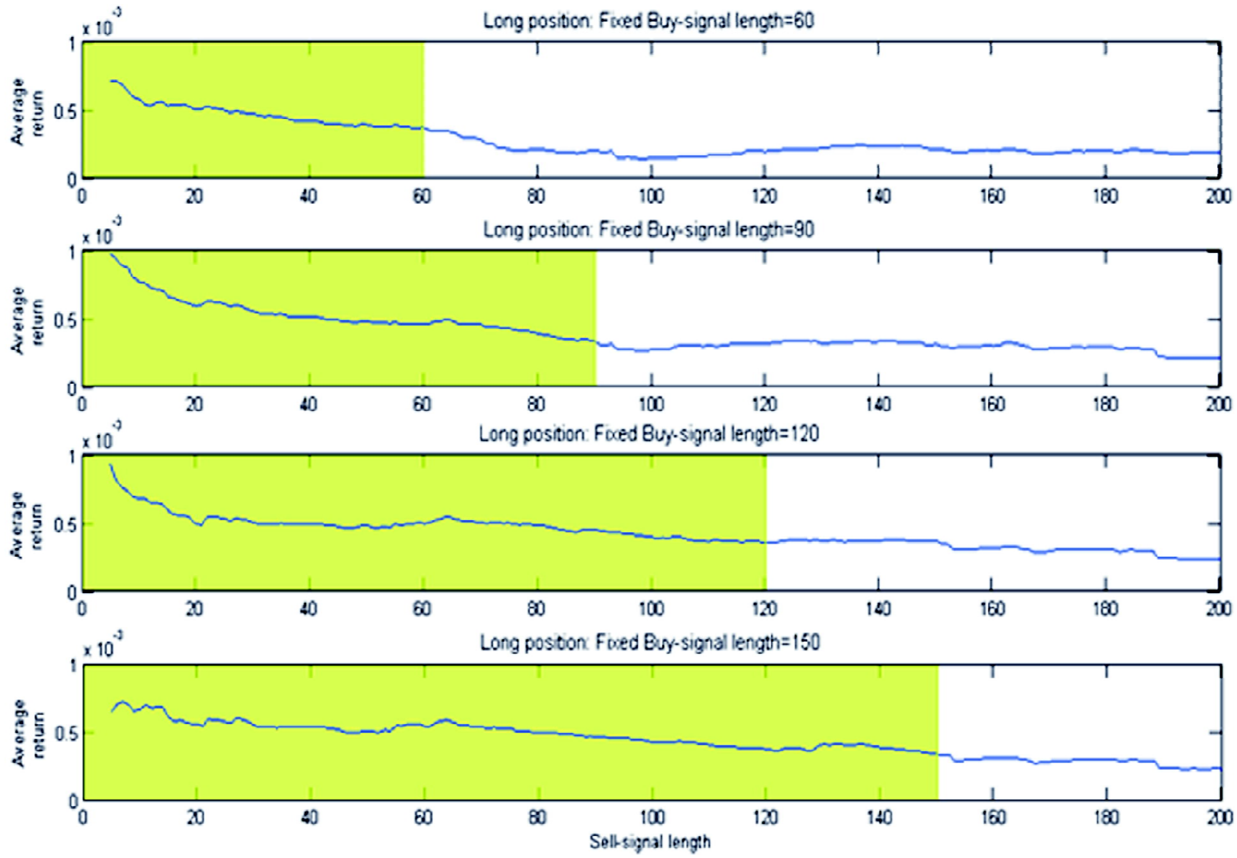

Figure 1: Averaged return of Long position achieved by various MA length for locating ending time point

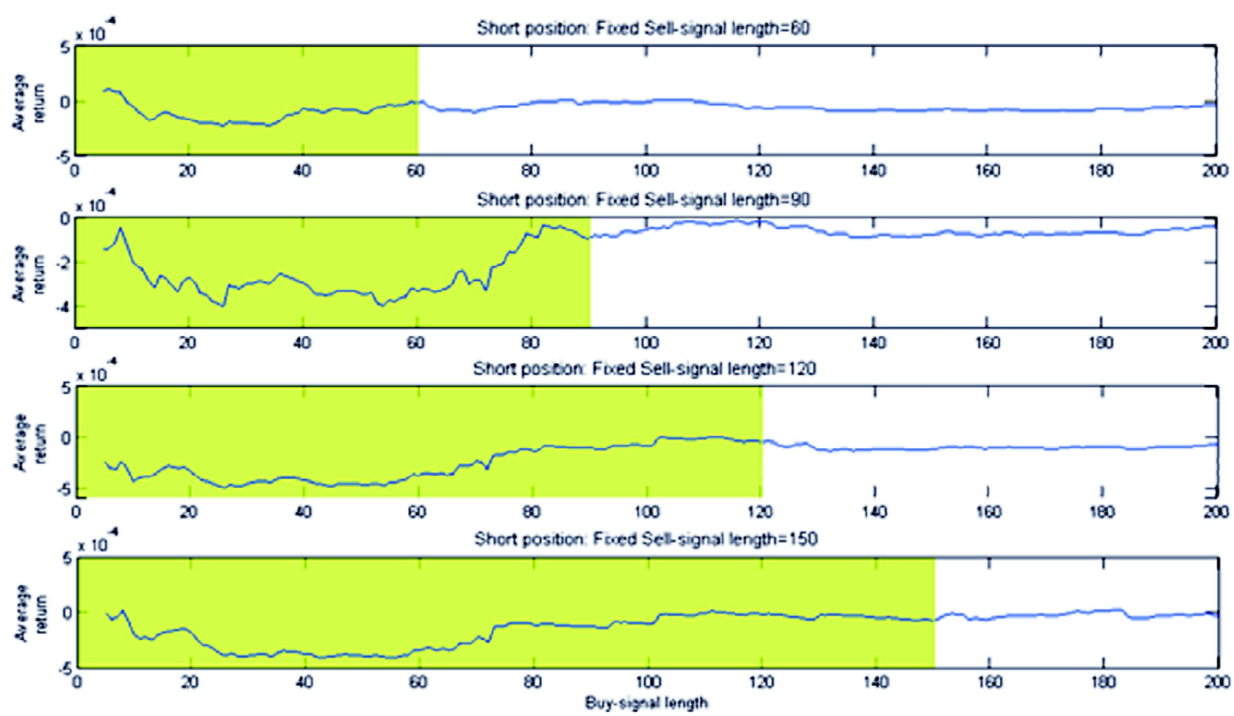

Figure 2: Averaged return of Short position achieved by various MA length for locating ending time point

Figure 3. The upper bound of Long positions identified by each buy-signal length value p_L is found by searching the best result among all possible asymmetric length (*i.e.* q_L {5, 6, ..., 200}). The calculation of upper bounds of Short positions follows the same logic.

The upper plot in Figure 3 shows the upper bounds of Long positions and the lower plot shows the results of Short positions. The two lines in each plot represent the upper bounds of average return from the Asymmetric approach and the average returns from the Symmetric approach. For the Long positions, it can be observed that the symmetric approach achieves the best performance in a very short length (*i.e.* length = 6) and it gives roughly the same results for lengths longer than 10. The Asymmetric approach can provide larger returns in all lengths, especially for the lengths between 90 to 120. The performance improvement for the Asymmetric approach over the Symmetric approach can be over 160% under a large range of lengths. On the other hand, the improvements in Short positions are not as obvious as those observed in Long positions. The improvements for over half of the length cases are less than 40%. The results show that the Asymmetric approach gives better improvements on identification of Long positions than Short positions.

4.3. Comparison between Optimal Symmetric Approach and Optimal Asymmetric Approach

The potential benefit of the Asymmetric approach is further investigated by comparing the best results achieved by the two approaches in terms of overall averaged returns from both Long and Short positions.

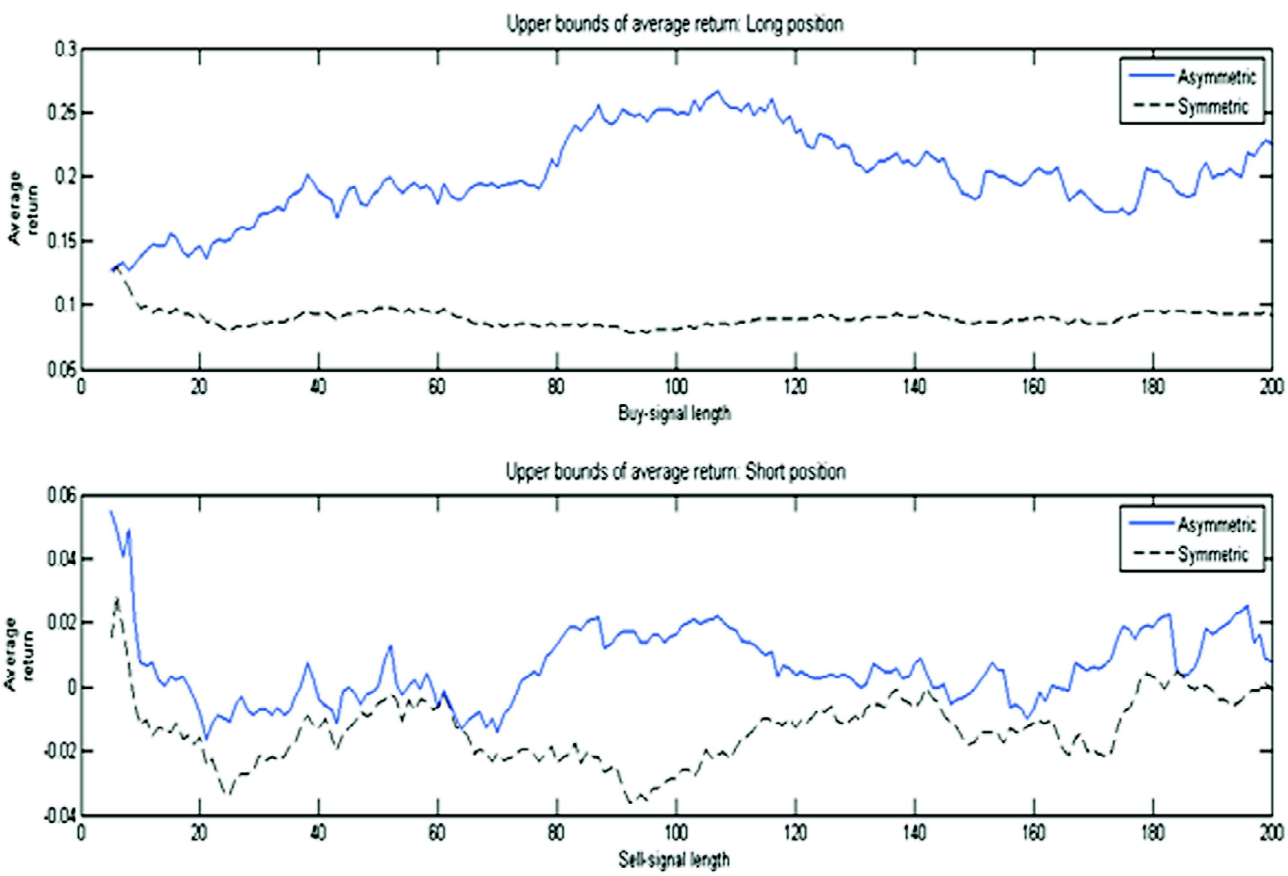

Figure 3: Upper bounds of average return of Long and Short positions

It has been demonstrated that the Asymmetric approach helps to improve the average return of both Long and Short positions in the previous subsection. This subsection focuses on demonstrating the differences between the Symmetric and the Asymmetric approach when they are used under an optimized setting.

The optimized setting for Symmetric approach is considered to be the largest average return achievable by setting the MA length from 5 to 200. The optimized result of the Symmetric approach (OPT-S) is defined as:

$$OPT - S = \max_{n} f_s\left(S_t(n)\right) \quad \text{(Eqt. 4)}$$

where $f_S(\cdot)$ represents a function calculating the average return achieved by using the MA series $S_t(n)$ as an input to identify Long and Short position. And, the variable $n = \{5,6,7, ... 200\}$.

The optimized result of the Asymmetric approach (OPT-A) is defined as the sum of the best results achieved in both Long and Short positions[6].

$$OPT - A = \max_{p_L, q_L} f_{Long}\left(S_t\left(p_L\right), S_t\left(q_L\right)\right) + \max_{p_S, q_S} f_{Short}\left(S_t\left(p_S\right), S_t\left(q_S\right)\right) \quad \text{(Eqt. 5)}$$

where $f_{\text{Long}}(\cdot)$ calculates the average return of Long positions achieved by using 2 different MA series $S_t(p_L)$ and $S_t(q_L)$ as inputs. The $f_{Short}(\cdot)$ calculates the average return of Short positions achieved by using other MA series $S_t(p_S)$ and $S_t(q_S)$ as inputs.

The empirical results of different Moving Average calculation methods are tabulated individually. Table 3, 4 and 5 shows the results of Simple Moving Average, Exponential Moving Average and Triangular Moving Average methods respectively. The proportion of days with positive returns and the average return are tabulated in the upper part and the lower part of each table. Rows with the label 'Historical' represent results obtained by holding Long positions on all the 'historical' days (Buy-and-hold strategy). The time period for comparing the performance begins with a day that both OPT-A and OPT-S give valid data.

The proportions of positive returns of OPT-S and OPT-A indirectly reflect the correctness of locating the uptrend and downtrend. If a strategy accurately suggests Long positions for uptrends and Short positions for downtrends, the proportion of positive returns achieved by the strategy will be 100%. A low proportion indicates a poor performance of a strategy. It can be seen that the OPT-A always provide a better performance than OPT-S in most circumstances, even we are optimizing on their average returns but not on their proportions.

Table 3
Simple Moving Average method -OPT-S vs. OPT-A

	S&P500	*FTSE*	*N225*	*DAX*	*TSX*	*ASX*	*HIS*
Prop. of +ve returns							
Historical	52.59%	52.52%	51.54%	53.32%	53.78%	52.59%	51.85%
OPT-S	51.31%	50.33%	52.46%	51.71%	54.46%	51.39%	52.14%
OPT-A	52.76%	51.62%	53.10%	51.64%	55.88%	53.56%	53.33%

Contd. table 3

	S&P500	*FTSE*	*N225*	*DAX*	*TSX*	*ASX*	*HIS*
Average return							
Historical	0.0622	0.0580	0.0164	0.0736	0.0577	0.0524	0.0731
OPT-S	0.0730	0.0495	0.0920	0.0853	0.1950	0.0439	0.2716
OPT-A	0.2106	0.1328	0.2226	0.2442	0.3148	0.1896	0.4924
Improvement %	188.54%	168.61%	142.02%	186.42%	61.49%	331.51%	81.32%
p-value (Welch's t-test)	0.0050†	0.1027	0.0581*	0.0910*	0.0818*	0.0094†	0.0828*

† and * indicate that the result is significance at 5% and 10% significance level respectively.

Table 4
Exponential Moving Average method - OPT-S vs. OPT-A

	S&P500	*FTSE*	*N225*	*DAX*	*TSX*	*ASX*	*HIS*
Prop. of +ve returns							
Historical	52.67%	52.51%	51.57%	53.30%	53.86%	52.30%	51.88%
OPT-S	51.54%	50.52%	52.07%	52.69%	54.53%	50.83%	52.58%
OPT-A	52.99%	52.65%	53.42%	52.15%	54.97%	53.59%	53.80%
Average return							
Historical	0.0654	0.0579	0.0153	0.0739	0.0601	0.0443	0.0739
OPT-S	0.0786	0.0405	0.0946	0.0810	0.1933	0.0505	0.2722
OPT-A	0.2098	0.1504	0.2360	0.1820	0.2654	0.1712	0.4243
Improvement %	166.90%	271.61%	149.48%	124.67%	37.29%	238.82%	55.91%
p-value (Welch's t-test)	0.0133†	0.0245†	0.0530*	0.1514	0.1224	0.0737*	0.0463†

† and * indicate that the result is significance at 5% and 10% significance level respectively.

Table 5
Triangular Moving Average method - OPT-S vs. OPT-A

	S&P500	*FTSE*	*N225*	*DAX*	*TSX*	*ASX*	*HIS*
Prop. of +ve returns							
Historical	52.61%	52.47%	51.53%	53.33%	53.83%	52.48%	51.84%
OPT-S	51.17%	50.14%	52.36%	52.51%	54.67%	51.12%	52.46%
OPT-A	51.01%	52.24%	51.99%	50.87%	57.14%	54.83%	52.86%
Average return							
Historical	0.0628	0.0563	0.0161	0.0744	0.0580	0.0488	0.0726
OPT-S	0.0717	0.0392	0.0893	0.0749	0.2116	0.0366	0.2954
OPT-A	0.1610	0.1941	0.2073	0.1958	0.3040	0.2144	0.5206
Improvement %	124.69%	395.32%	132.19%	161.55%	43.62%	485.92%	76.26%
p-value (Welch's t-test)	0.0584*	0.0156†	0.1039	0.1456	0.1289	0.0141†	0.1033

† and * indicate that the result is significance at 5% and 10% significance level respectively.

The magnitude of improvements made by OPT-A over OPT-S is obvious, ranging from 60% to 180% for SMA method, 37% to 270% for EMA method and 40% to 480% for TMA method. The results of one-tailed Welch's *t*-test also indicate a strong support on the OPT-A approach. For the longest data set, S&P 500, all three MA methods give statistically significant results at either 5% or 10% significance level. Furthermore, the average return of OPT-A is showed to be statically significant at 6 out of 7 cases in SMA method, 5 out of 7 cases in EMA method and 3 out of 7 cases in TMA method respectively. In addition, OPT-A gives much better average returns than the 'Buy-and-hold' strategy in all the circumstances. The empirical results support that the Asymmetric approach can provide better average returns than the Symmetric approach when it is employed effectively by selecting appropriate length pairs.

5. CONCLUSIONS AND RECOMMENDATIONS

This paper addresses the issue of asymmetrical information content observed in uptrend and downtrend patterns which is caused by investors' risk aversion preference. People tend to close their long positions once they perceive a formation of downturn in the market and large sudden price drops can always be observed near the end of uptrends. The empirical data from 8 different stock markets demonstrate that the average values of absolute price changes of days with negative returns are significantly larger than those obtained from days with positive returns. The existence of the asymmetrical information content indirectly supports the use of distinct ways to identify uptrends and downtrends separately.

A new Moving Average trading strategy is proposed to model the ending time points of uptrends and downtrends under an asymmetrical setting. Investigation on the effect of using different MA lengths under 3 moving average calculation methods is carried out. The results show that a more responsive way (*i.e.* using a shorter MA length) to locate the ending time points of uptrends always helps to achieve a better average return. Based on our empirical data, a short MA length (*i.e.* 5-7) for generating sell-signals always gives good performance in uptrend identification. About downtrend identification, however, not any consistent clues in selecting appropriate MA lengths can be found. Moreover, it is shown that the asymmetric approach provides much larger improvement on uptrend identification than downtrend identification in general.

The potential benefits of the proposed approach are further studied by comparing the total average return obtained from both Long and Short positions under optimized parameter settings. The empirical results support that the Asymmetric approach can provide much better average returns (e.g. over 120% improvement for S&P500 data set) than the Symmetric approach when it is employed effectively under appropriate length pairs.

The findings in this paper provide some insights on the use of asymmetric setting for trend identification. It is possible that the use of asymmetric setting will also improve the performances obtained from other technical trading strategies. On the other hand, the existence of asymmetrical information content in uptrends and downtrends can be considered as a hint for selecting suitable input data and optimization targets for machine-learning trading systems. It is suggested that distinct structures should be used to model the Long and Short positions separately.

NOTES

1. Other works on MA strategy include LeBaron (1999); Fang and Xu (2003); Cesari and Cremonini (2003); Marshall and Cahan (2005); Zhu and Zhou (2009)

2 Dempster and Jones (2001) demonstrated the use of genetic programming to build an adaptive trading system by making use of several trading strategies; Zhang and Zhou (2004) discussed the potential usage of MA strategy in data mining financial applications; R. Dash and P. Dash (2016) studied the performance of using machine learning techniques to integrate technical trading strategies.

3. AGARCH (Asymmetric GARCH) is proposed by Engle (1990); EGARCH (Exponential GARCH) is proposed by Nelson (1991); GJR-GARCH is proposed by Glosten, Jagannathan and Runkle (1993); NAGARCH (Nonlinear Asymmetric GARCH) is proposed by Engle and Ng (1993); APARCH (Asymmetric Power ARCH) is proposed by Ding, Granger and Engle (1993), Reference to other volatility models can be found in Bollerslev (2008) paper.

4. The empirical results can be replicated using the publicly available data obtainable from Yahoo Finance and the MATLAB tsmovavg() function.

5. Graphical results generated by using other data sets and MA methods are available on request.

6. It is noted that the formulation for calculating the average return achieved by the use of 2 different pairs of MA lengths in eqt. 5 can be further improved. The formulation of OPT-A in eqt. 5 searches for 2N2 combinations only but it can be modified to search for N4 combinations by optimizing both Long and Short positions simultaneously. It is likely that conducting an exhaustive search on N4 solution space will give a better result (N is the size of feasible MA lengths. This paper investigates MA length from 5 to 200 and therefore N = 196).

REFERENCES

Bollerslev, T., (2008), Glossary to arch (garch), *CREATES Research Papers*, (49), Available at: http://faculty.chicagobooth.edu/jeffrey.russell/teaching/Finecon/readings/glossary.pdf.

Brock, W., Lakonishok, J. and LeBaron, B., (1992), Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *The Journal of Finance*, 47(5), pp. 1731–1764.

Cesari, R. and Cremonini, D., (2003), Benchmarking, portfolio insurance and technical analysis: A Monte Carlo comparison of dynamic strategies of asset allocation. *Journal of Economic Dynamics and Control*, 27(6), pp. 987–1011.

Dash, R. and Dash, P.K., (2016), A Hybrid Stock Trading Framework Integrating Technical Analysis with Machine Learning Techniques. *The Journal of Finance and Data Science*, 2(1), pp. 42–57.

Dempster, M. A. H. and Jones, C.M., (2001), A real-time adaptive trading system using genetic programming. *Quantitative Finance*, 1(4), pp. 397–413.

Ding, Z., Granger, C.W.J. and Engle, R.F. (1993), A Long Memory Property of Stock Market Returns and a New Model, *Journal of Empirical Finance*, 1, 83-106.

Engle, R.F. (1990), Discussion: Stock Market Volatility and the Crash of '87, *Review of Financial Studies*, 3, 103-106.

Engle, R.F.and Ng, V.K. (1993), Measuring and Testing the Impact of News on Volatility, *Journal of Finance*, 48, 1749-1778.

Fang, Y. and Xu, D., (2003), The predictability of asset returns: An approach combining technical analysis and time series forecasts. *International Journal of Forecasting*, 19(3), pp. 369–385.

Fong, W.M. and Yong, L.H.M., (2005), Chasing trends: Recursive moving average trading rules and internet stocks. *Journal of Empirical Finance*, 12(1), pp. 43–76.

Glosten, L.R., Jagannathan, R. and Runkle, D. (1993), On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, *Journal of Finance*, 48, 1779-1801.

Gunasekarage, A. and Power, D.M., (2001), The profitability of moving average trading rules in South Asian stock markets. *Emerging Markets Review*, 2(1), pp. 17–33.

Lai, M.M. and Lau, S.H., (2006), The profitability of the simple moving averages and trading range breakout in the Asian stock markets. *Journal of Asian Economics*, 17(1), pp. 144–170.

LeBaron, B., (1999), The Stability of Moving Average Technical Trading Rules on the Dow Jones Index. *Derivates Use, Trading and Regulation*, 5(4), pp. 1–14.

Levich, R.M. and Thomas, L.R., (1991), The Significance of Technical Trading-Rule Profits in the Foreign Exchange Market: A Bootstrap Approach. *NBER Working Paper,* no. 3818.

Marshall, B.R. and Cahan, R.H., (2005), Is technical analysis profitable on a stock market which has characteristics that suggest it may be inefficient? *Research in International Business and Finance*, 19(3), pp. 384–398.

Marshall, B.R., Cahan, R.H. and Cahan, J.M., (2008), Does intraday technical analysis in the U.S. equity market have value? *Journal of Empirical Finance*, 15(2), pp. 199–210.

Nelson, D.B. (1991), Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica*, 59, 347-370.

Tim, B., (2008), Glossary to ARCH (GARCH), *Center for Research in Econometric Analysis of Time Series*, (49).

Zhang, D. and Zhou, L., (2004), Discovering golden nuggets: Data mining in financial application. *IEEE Transactions on Systems*, Man and Cybernetics Part C: Applications and Reviews, 34(4), pp. 513–522.

Zhou, N. *et al.*, (2015), Evolution of high-frequency systematic trading: a performance-driven gradient boosting model. *Quantitative Finance*, 15(8, SI), pp. 1387–1403.

Zhu, Y. and Zhou, G., (2009), Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, 92(3), pp. 519–544.