Predictability of Asia Pacific Stock Market Indices Futures using Signals from A Dynamic Volatility Indicator, Adjustable Moving Average, AMA’

Jacinta Chan Phooi M’ng and Rozaimah Zainudin

Abstract— This research studies the daily stock market indices futures contracts’ returns from the Asia Pacific countries, namely Australia’s SPI Futures (SPIF), Hong Kong’s Hang Seng Futures (HSF), Japan’s Nikkei 225 Futures (NikkeiF), Korea’s KOSPI Futures (KOSPIF), Malaysia’s FBMKLCI30 Futures (FKLI) and Singapore’s SImSCI Futures (SIMSCIF), from 2008 to 2012 to examine the predictability of these time series returns using some simple technical analysis trading systems like moving average trading rules, and a new innovated dynamic volatility trading system, called Adjustable Moving Average (AMA’). AMA’ adjusts to the volatility in the prevailing market condition to avoid some whipsaws in range trading and to enter into the new trends early in trend trading. By using the past trading signals from these moving averages rules, evidences of abnormal returns after transaction costs, the passive buy-and-hold are found in these time series’ returns; especially more so for AMA’. In particular, for this study period, AMA’ generates more abnormal returns for Hang Seng Futures, Nikkei Futures and SPI Futures than the other trading rules. The results from this research suggest that it is worthwhile to investigate more adjustable trading rules, the profitability of these rules, and the predictability of time series using these adjustable rules.

Keywords— Automated adjustable moving average, Automated algorithmic trading, Futures timeseries returns, Technical analysis indicators.

I. INTRODUCTION

Technical analysis has been a part of financial practice for many decades, even though this discipline has not received the same level of academic scrutiny and acceptance as other more traditional approaches like fundamental analysis; thus one of the greatest gaps between the academicians and market practitioners is the vast difference in levels of acceptance of technical analysis [1]. As some academic studies suggest, technical analysis can be an effective method for extracting useful information from market prices and volumes [2, 3, 4, 5, 6, 7, 8, 9, 10 and 11]. Using simple moving average concept, technical analysis offers market practitioners established trading rules to decipher market's behavioural patterns while maintaining profit maximization with a minimal loss situation [7]. However, Brock, Lakonishok and LeBaron [4] highlights the drawback of this common moving average trading rule method where it practically ignores the element of ever changing volatility characteristic that is present in financial markets. Market volatility plays a vital role in influencing the return predictability [12]. Balsara, Carlson and Rao [14] discusses the importance of new trading systems that can align with the prevailing market condition, whether it is a ranging or a trending market. Empirical evidence highlights the importance of new trading rules system that able to account the dynamic market condition [14 and 15]. Hence, this study introduces an adjustable volatility based algorithm into an adjustable moving average trading system called Adjustable Moving Average (AMA’). AMA’ generates automatically adaptive parameters to fit historical and current data and thus market condition.

The objectives of this research paper are to investigate if these Asia Pacific stock index futures contracts follow some trends and to test if in the long run, algorithm technical trading rules perform better than the passive buy-and-hold strategy advocated by random walk hypothesis. Specifically, we test if AMA’ generates more net profits for the stock index futures contracts for the period 2008 to 2012 than some of the other common technical analysis indicators. Thus, we begin with testing the trading rules specified by Brock, Lakonishok and LeBaron [4] and others like Appel [16], Kaufman [17] ranging from simple moving average trading systems to a newly innovated algorithm trading model, AMA’, to verify if these trading systems generate net profits in the long run; then we compare these models profit performance against the passive buy-and-hold strategy in the long run. Based on the results of the back tests for these stock index futures contracts, most of these trading systems generate positive net returns after transaction costs.

In the next section, a brief investigation on the properties of the stock index futures contracts is described, followed by the trading system methods used. Then the results are presented and discussed. Finally, a conclusion wraps up this research paper.

II. DATA DESCRIPTION

This study uses the closing prices of FTSE Bursa Malaysia Kuala Lumpur Composite Index Futures (FKLI) from Malaysia, KOSPI Futures from Korea, Nikkei Futures from Japan, SiMSCI Futures from Singapore and SPI Futures from Australia for the period of 01/02/2008 to 12/31/2012. The
daily closing prices are transformed into daily returns using log(Close_{t}/Close_{t-1}) where Close_{t} and Close_{t-1} represent current close price and previous close price. The statistical characteristics of the daily returns from these stock index futures contracts derived from a preliminary data analysis performed are presented in Table I. Based on the data analysis, the existence of non-normality distribution in these six tested series cannot be rejected.

### Table I: Descriptive statistics of daily returns from 1/2/2008 to 12/31/2012

<table>
<thead>
<tr>
<th></th>
<th>FKLI</th>
<th>HSF</th>
<th>KOSPIF</th>
<th>NIKKEIF</th>
<th>SiMSCIF</th>
<th>SPIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0002</td>
<td>0.0003</td>
<td>0.0002</td>
<td>0.0003</td>
<td>0.0002</td>
<td>0.0001</td>
</tr>
<tr>
<td>Median</td>
<td>0.0001</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.0710</td>
<td>-0.0104</td>
<td>-0.0104</td>
<td>-0.0104</td>
<td>-0.0104</td>
<td>-0.0104</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.0710</td>
<td>0.0104</td>
<td>0.0104</td>
<td>0.0104</td>
<td>0.0104</td>
<td>0.0104</td>
</tr>
</tbody>
</table>

Testing the observation that the standard deviations of these daily returns are non-constant and tend to vary with time, we find evidence of this non-constant characteristic in the standardized residuals, presented in the Table II. Mandelbrot [18] reports that volatilities tend to cluster in periods of high volatilities, followed by periods of low volatilities and vice versa. From the evidence of these dynamic volatilities, it can be deduced that using a constant moving average throughout the whole study period is not suitable for producing the best profitable results. Therefore, this research proposes to adjust the moving average for each different period according to the volatilities characteristic of that particular period using the prevailing Efficacy Ratio (EffR) which is derived from the standard deviations of two periods (refer to III. Estimation Techniques).

### Table II: Descriptive statistics of standardized residuals from 1/2/2008 to 12/31/2012

<table>
<thead>
<tr>
<th></th>
<th>FKLI</th>
<th>HSF</th>
<th>KOSPIF</th>
<th>NIKKEIF</th>
<th>SiMSCIF</th>
<th>SPIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kurtosis</td>
<td>80.7423</td>
<td>80.0183</td>
<td>80.3293</td>
<td>80.0173</td>
<td>80.0173</td>
<td>80.0173</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.0384</td>
<td>0.0173</td>
<td>0.0173</td>
<td>0.0173</td>
<td>0.0173</td>
<td>0.0173</td>
</tr>
<tr>
<td>Probability</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

Simple 21 Days Moving Average (SMA)

The most common trading system is the Variable Moving Average (1,21,0%) used Brock, Lakonishok and LeBaron [4], (1 represents the current closing price, 21 represents 21-days simple moving average and 0% represents 0% from the 21-days simple moving average). 20 or 21 days is used because it represents one (1) month of trading days. The average of 21 days of closing is computed, and it is then compared to the current closing price. If the current closing price exceeds the 21-days SMA, a buy signal is generated. If the current closing price is below the 21-days SMA, then the signal is to sell.

3 and 21 Days Moving Average Crossover (MAC)

The other common trading system is the Variable Moving Average (3,21,0%) tested by Brock, Lakonishok and LeBaron [4], with a slightly different condition from SMA. 3 and 21 days of simple moving averages are estimated and compared. If the 3-days SMA exceeds the longer 21-days SMA, then a buy signal is generated, otherwise a sell. The lengths, 3 and 21 are arbitrary chosen.

Moving Average Convergence Divergence (MACD)

Appel [16] introduces MACD in the late 1970s. MACD can be estimated by first computing MACD by subtracting a shorter-term (12-days) exponential MA from a longer-term (26-days) exponential MA, and then computing the Signal Line by calculating 9-days exponential averages of these differences (MACD). A buy signal is generated when MACD crosses up above Signal Line and a sell signal is generated when MACD crosses below the Signal Line.

Kaufman Adaptive Moving Average (KAMA)

Kaufman [17], one of the first to posit a non-constant moving average, approarizes different weightages to the current data and past smoothened data series according to Efficiency Average (SMA), Moving Average Crossover (MAC), Trading Range Breakout (BO), 1% Bands from Moving Average (MA1%); 2) Three (3) innovated methods used by Appel [16] (Moving Averages Convergence Divergences (MACD), Kaufman [17] (Kaufman Adaptive Moving Average (KAMA)), Chan [19] (Standard Deviation Bands Z-Statistics (BBZ)); and 3) One (1) newly innovated method proposed by this research (Adjustable Moving Average (AMA)).

The aims are to compare the returns’ performances of these (8) trading systems against: a) the threshold buy-and-hold (BH) for abnormal profit results, and b) each other to identify the best algorithm trading system. The best trading system will fulfill the following criterions: i) it should not encounter large losses, or show net large loss in any of the years; ii) it should work well in practice as in testing; iii) it can adjust automatically to the parameter shifts; and iv) slippage and transaction costs should be taken into account.
Ratio. Efficiency Ratio (ER) takes into account the amount of the closing prices’ movement within n periods in relation to the sum of all daily movements.

\[
KAMA_n = \alpha \text{ER} C_t + (1-\alpha) \text{ER} KAMA_{n-1}
\]

where

\[
\alpha = \left[ \left( \frac{2}{3} - \frac{2}{3T} \right) + \frac{2}{3T} \right]^{-2}
\]

\[
\text{ER} = \frac{(C_t - C_{t-1})}{\sum |C_{t-i}|}
\]

C_t is the current closing price and C_{t-1} is the closing price at period t-1. If the current closing price is above KAMA_n, a buy signal is generated. If the current close is below the KAMA_n, then the signal is to sell.

Trading Range Breakout (BO)

Trading Range Breakout trading system (BO) uses the breakout from recent highs or lows, to identify new trading opportunities (similar application in Donchian [20] and Brock, Lakonishok and LeBaron [4]). Using a 20-days trading range breakout rule, a buy signal is generated when the price breaks below the upper 1% band. The upper and lower 1% bands are calculated as follows:

\[
\text{BZ} = \text{MA}(1,21,1\%) + 1 \times \text{stdev} \text{BZ}, \quad \text{LBZ} = \text{MA}(1,21,1\%) - 1 \times \text{stdev} \text{BZ}
\]

BB Z-Test-Statistics (BBZ)

To avoid trading unprofitably during range periods, BBZ [19] generates trading signals only when volatility increases, that is, when the closing price moves above +1 or below -1 standard deviation band. BBZ first computes the 21-days MA and 1 standard deviation and then adds 1 standard deviation to the 21-days MA to derive the upper band and to deduct 1 standard deviation from the 21-days MA to obtain the lower band. If the closing price is above the upper band, then the signal is to buy and when the closing price is below the upper band, the signal is to exit long. If the closing price is below the lower band, then the signal is to sell and when the closing price is above the lower band, the signal is to exit short.

Adjustable Moving Average' (AMA')

While KAMA uses Efficiency Ratio to apportion the weights of the current data and past smoothed data series, AMA' adjusts the length of the moving average for each different period according to the prevailing Efficacy Ratio (EffR).

\[
\text{EffR} = \frac{LT\text{EffR} \times \text{STEffR}}{\text{LT} + \text{ST}}
\]

where LT EffR and ST EffR represent the long term standard deviation and short term standard deviations respectively. This study proposes to use a ratio of 34-days LT EffR and 6-days for ST EffR. EffRatio dynamically and automatically varies to suit the current market condition. This adaptability potentially addresses the most important common problem encountered by traders in gauging whether the market is ranging or beginning to trend. If the current closing price is above AMA', then a buy signal is generated. If the current closing is below AMA', then the signal is to sell.

IV. EMPIRICAL RESULTS

The results show that the objectives of this research which are to find abnormal returns of the eight trading systems above that of passive buy-and-hold (BH) (considering transaction costs); and to show how the new AMA’ model outperforms the other tested trading systems, have been achieved. Table III shows all the trading systems’ results surpass the BH and that KAMA outperforms the rest of the trading systems and marginally against AMA’ by 24 index points over the five years period. Tables IV, VI and VII show AMA’ outperforming BH and also the other trading systems for Hang Seng Futures, Nikkei Futures and SPI Futures by relatively large margins. This indicates that AMA’ may be an ideal trading system in fast changing markets like Hang Seng Futures and Nikkei Futures. However, for markets like KOSPI Futures and SiMSCI Futures, slower trading systems like MACD and MAC are more useful as shown in Tables V and VII.
It is noted in studies [9] and in real life trading that transaction costs account for a chunk of the trading losses and thus, it would unrealistic if transaction costs are not included in this study. The transaction costs are converted into the nearest index point(s) to account for brokerage commission including exchange and clearing fees as well as slippage. For example, in the case of FKLI, the maximum transaction cost for a 2 way transaction (in and out of the position) amounting to RM50 is equivalent to 1 index point. Similarly, 1 index point cost SPI Futures, while 10 index points are applied to most profitable trading model.

Table IX: Mean Returns After Transaction Costs

<table>
<thead>
<tr>
<th>SID</th>
<th>MA1%</th>
<th>BBZ</th>
<th>AMA'</th>
</tr>
</thead>
<tbody>
<tr>
<td>FKLI</td>
<td>2.02%</td>
<td>7.26%</td>
<td>7.47%</td>
</tr>
<tr>
<td>HSSF</td>
<td>-4.83%</td>
<td>0.41%</td>
<td>-3.42%</td>
</tr>
<tr>
<td>KeepF</td>
<td>1.99%</td>
<td>-6.83%</td>
<td>-2.60%</td>
</tr>
<tr>
<td>Nikkei</td>
<td>3.81%</td>
<td>7.15%</td>
<td>6.04%</td>
</tr>
<tr>
<td>SIMSCIF</td>
<td>-3.09%</td>
<td>9.09%</td>
<td>9.79%</td>
</tr>
<tr>
<td>SPIF</td>
<td>-5.42%</td>
<td>-5.29%</td>
<td>-4.99%</td>
</tr>
<tr>
<td>Total</td>
<td>-9.84%</td>
<td>11.01%</td>
<td>9.99%</td>
</tr>
</tbody>
</table>

Table X shows the mean returns’ differences from the buy-and-hold. The mean returns differences from BH are computed by taking the difference between the trading system’s mean return and the mean return of the respective BH. Except for KOSPI Futures and Nikkei Futures, all the trading systems outperform the BH for selected Asia Pacific indices futures. In terms of total performance across the selected stock index futures contracts, Table X shows that AMA’ is the only trading model that generates abnormal profits. This indicates that AMA’ is a robust trading model and can be used for all these markets. AMA’ outperforms SMA, the second best trading system in terms of profits, by a relatively large margin and thus, can be taken into consideration as a viable trading model for the professional model trading desk of financial institutions.

Table X: Differences of Mean Returns From Buy-and-Hold after Transaction Costs

<table>
<thead>
<tr>
<th>SID</th>
<th>MA1%</th>
<th>BBZ</th>
<th>AMA’</th>
</tr>
</thead>
<tbody>
<tr>
<td>FKLI</td>
<td>5.24%</td>
<td>5.41%</td>
<td>1.63%</td>
</tr>
<tr>
<td>HSSF</td>
<td>5.26%</td>
<td>1.43%</td>
<td>1.16%</td>
</tr>
<tr>
<td>KeepF</td>
<td>-9.82%</td>
<td>-4.67%</td>
<td>6.35%</td>
</tr>
<tr>
<td>Nikkei</td>
<td>3.30%</td>
<td>-2.33%</td>
<td>-6.46%</td>
</tr>
<tr>
<td>SIMSCIF</td>
<td>12.18%</td>
<td>12.79%</td>
<td>4.81%</td>
</tr>
<tr>
<td>SPIF</td>
<td>0.11%</td>
<td>1.03%</td>
<td>1.90%</td>
</tr>
<tr>
<td>Total</td>
<td>23.84%</td>
<td>18.83%</td>
<td>18.21%</td>
</tr>
</tbody>
</table>

V. CONCLUSION

The profitable results computed in this research are entirely consistent with the findings reported by Lukac, Broersen, Irwin [2], Brock Lakonishok and LeBaron [4], and Bessembinder and Chan [6] where the presence of abnormal returns using various technical trading rules are found. Considering the time varying condition in the markets and the need to program trading models to be adaptive to the market, like the genetic programmes done by Gencay and Stengos [7], machine learning by Andrade-Felix and Fernandez-Rodriguez [8] and the dynamic MACD standard deviation embedded in MACD indicator for accurate adjustment by Gandolfi, Rossolini, Sabatini and Caselli [21], this study introduces AMA’ which outperforms the simple moving averages, the trading range breakout trading system and the traditional MACD for the stock indices futures in Asia Pacific region for the period between 2008 and 2012.

AMA’ is designed to address some of the common problems encountered by most trend trading systems such as floods of orders generated by common trading systems (like SMA), being whipsawed in range market and failed to correctly time the trend (entering the trend too late and exiting the trend too early). AMA’ has the ability to adjust accordingly in different conditions, which is why it is considered robust and performs better than other models. Therefore, with its ability to adapt to market conditions, AMA’ could be a valuable tool for financial markets.
market conditions and across different time frames. Based on the results, this research ascertains that the price movements of these six stock index futures contracts tested are not random. The trading systems from ranging simple moving averages to the newly innovated AMA can be used to compute the abnormal returns arising from trending behaviour. Finally, AMA is a robust adaptive algorithm trading model that can be implemented based on past and current empirical evidence and it is possible that it can contribute to the profits of the model trading desk.

The ability of AMA to adjust according to the prevailing market condition, points a new direction for research in incremental machine learning trading systems. New adaptive new trading models like AMA can be applied immediately on any professional model trading desk. Despite good preliminary results, future research can explore and find specific algorithms that cater for automatic determination of the length of the long and short term standard deviations, and thus the length of the variable moving average. With artificial intelligent algorithms, neural networks can learn the behaviour of the market, whether it is trending or ranging, and adjust the algorithms automatically according to the prevailing market condition.

REFERENCES


