EMD-Candlestick: methodology and applications

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Abstract

The paper proposes an application of Empirical Mode Decomposition in technical analysis. The EMD-candlestick is designed to replace the traditional candlestick as the signal generators in technical trading strategies to improve the profitability. We investigate a representative set of technical trading strategies, including moving average, trading range break-out, relative strength index, and intraday and interday trading rules, using the securities included in Dow Jones Industrial Average from 1993 to 2012. Empirical results show that variable length moving average rules, relative strength index rules, and intraday and interday trading rules are more profitable if EMD-candlestick is used than if the traditional candlestick is used.

1 Introduction

Since Huang *et al.* (1998) introduce the empirical mode decomposition (EMD), there are many successful applications of this methodology in various areas. Echeverria *et al.* (2001) suggest the use of EMD and the associated Hilbert spectral representation as time-frequency analysis tools for heart rate variability data. Nunes *et al.* (2003) extend the one-dimensional decomposition to two-dimensional data and apply it to the texture extraction and image filtering. Coughlin and Tung (2004) extract a clear 11-year solar cycle signal from stratospheric data using EMD. Liang *et al.* (2005) apply EMD for the analysis of esophageal manometric time series in gastroesophageal reflux disease. Liu *et al.* (2006) apply EMD to analyze vibration signals for localised gearbox fault diagnosis and find that EMD is more effective than the often-used wavelet transform in detecting vibration signatures.

Since EMD is a powerful adaptive data analysis tool especially for non-stationary non-linear data, it has been applied in various areas in finance. Zhu (2006) studies a new technique of suspicious transaction detection by first decomposing the complex financial time series into intrinsic mode functions (IMF) and residue that represent different time scales like daily, monthly, seasonal or annual scale. Zhang *et al.* (2008) apply EMD to crude oil price analysis and explain the oil price as the composite of a long term trend, effect of a shock from significant events, and short term fluctuations caused by normal supply-demand disequilibrium. Guhathakurta *et al.* (2008) use EMD to analyse two financial time series and compare the probability distributions of their IMF phases and amplitudes. Drakakis (2008) applies EMD technique on Dow-Jones volume and makes some inferences on its frequency content. An introduction on EMD is given in Chan *et al.* (2014) where they also design a trading strategy using EMD and investigate its profitability using daily Hang Seng Index and China Shanghai Composite Index. In this context, we focus more on the technical analysis aspect and consider the EMD as a frequency pass filter.

In finance, technical analysis is a security analysis methodology to forecast the future price trend by using historical financial data, mainly price and volume. Many technical analysis tools are based in particular on the daily close prices to derive trading strategies. Empirical results of profitability of these technical trading strategies are mixed. Brock *et al.* (1992) show the forecasting ability of the moving average and the trading range break rules on the Dow Jones Industrial Average Index over a period of 90 years. Bessembinder and Chan (1995) extend Brock's study and find that the trading rules are successful in the emerging markets of Malaysia, Thailand and Taiwan. Some other empirical studies, including Sweeney (1988), Taylor and Allen (1992), Neely *et al.* (1997), show the usefulness of technical trading rules based on daily close price. However, Mills (1997), Ito (1999) and Marshall *et al.* (2008) find that the return of technical analysis trading strategies are insignificantly different from the return of buy-and-hold strategy. Park and Irwin (2007) review and summarize 95 modern studies on the profitability of technical analysis and observes that 56 of them find positive results, 20 of them obtain negative results, and the rest indicate mixed results.

In addition to the aforementioned rules that are based only on the past daily closing prices, there are also rules that includes daily high, low and open prices. A good representation of these four daily prices is the candlestick graph, a technical analysis tool credited to Munelusa Homma (see for instance Marshall *et al.* (2006)). The candlestick essentially is a summary of the daily performance of the underlying stock and is completely determined by the open price, close price, daily high, and daily low. Fiess and MacDonald (2002) investigate the informational content of these four prices and their values in forecasting volatility and future levels of daily exchange rates. Lam and Chong (2006) study the profitability of directional indicator which takes daily high, low and close prices to generate the signal. Lam *et al.* (2007) use all contents in the candlestick to examine whether the day's surge or plummet in stock price can serve as a market entry or exit signal and find the trading rules perform well in the Asian indices.

While the profitability of technical trading strategies is still a controversy, we attempt to improve their performance using EMD. One of the reasons why most technical analysis tools use candlestick as a building block is that they believe the candlestick to be a genuine summary of the daily performance of the stock. However, the noise within the intraday level may affect the use of the four prices as a summary. To this end, we hypothesize that the construction of candlestick using a less noisy level of data can generate more profitable technical trading strategies. We employ the EMD methodology to separate the information from the noise on intraday level data because of the following two reasons. Firstly, the EMD allows for local extraction of information and makes no assumption about linearity or stationarity as the classic Fourier analysis does. Secondly, intrinsic time scales of the data are used in the decomposition. Each resulting component has different average frequency and is defined by the amplitude variations in the original time series. Therefore, the EMD is an ideal data-adaptive tool to decompose real-time data and retrieve its frequency components that have actual physical significance. In our text, the EMD will be used as a low-pass filter to stock prices that filter out the noise and we define the candlestick constructed using EMD as EMD-candlestick.

The usefulness of the EMD-candlestick can be empirically tested with technical analysis. We follow the literature to identify a set of technical trading strategies that are based on the contents in candlestick. In this paper, we conduct empirical tests to determine whether the use of EMD-candlestick instead of the traditional candlestick can improve the profitability of these strategies.

The rest of the paper is organized as follows. Section 2 describes the EMD methodology and how it is applied to intraday financial data. Section 3 describes the data, the technical trading strategies we identify in the literature for the empirical tests and the hypothesis tests. Section 4 concludes our findings.

2 Empirical Mode Decomposition

The empirical mode decomposition (EMD), proposed by Huang *et al.* (1998), is a data-adaptive algorithm which decomposes a real-time signal into finite and often small number of intrinsic mode functions (IMFs) and a residue. A summary of EMD is given in Chan *et al.* (2014). IMF is defined as the function satisfying the following conditions:

1. The number of extrema and the number of zero-crossings are either equal or differ at most by one for any time interval.

2. The mean value of the upper envelope connected by local maxim and the lower envelope connected by local minima is zero.

Given a discrete signal $\mathbf{x} = (x_1, x_2, ..., x_n)$, the procedures for the EMD algorithm are:

1. Identify all the maxima and minima of $\mathbf{x}$.

2. Connect all maxima and minima respectively by cubic splines to form the upper envelop, $envelop_{max}$, and the lower envelop, $envelop_{min}$, respectively.

3. Calculate the local mean, denoted by $\mathbf{a} = (a_1, a_2, ..., a_n)$, of the upper and lower envelops.

4. Obtain the detail $\mathbf{d} = \mathbf{x} - \mathbf{a}$.

5. Check if $\mathbf{d}$ meets the conditions of IMF. If not, repeat Steps 1 to 4 using $\mathbf{d}$ as the new $\mathbf{x}$ until certain stopping criteria are satisfied. Different stopping criteria are proposed by Huang *et al.* (2003) and Rilling *et al.* (2003). In our research, we will adopt the criteria proposed by Rilling *et al.* (2003):

   - The number of extrema and number of zero-crossings differ at most by one.
   - The evaluation function $\sigma(t) < \theta_1$ for some prescribed fraction $(1 - \alpha)$ of the total duration, while $\sigma(t) < \theta_2$ for the remaining fraction. Here

     $$\sigma(t) = \frac{|(envelop_{max} + envelop_{min})|}{|(envelop_{max} - envelop_{min})|},$$

     and one can typically set $\alpha = 0.05,\ \theta_1 = 0.05$ and $\theta_2 = 0.5$.

   This step is often known as the *sifting process*.

6. The detail after the sifting process is called the first IMF $\mathbf{c}_1 = (c_{1,1}, c_{1,2}, \cdots, c_{1,n})$. Repeat the sifting process on the residue $\mathbf{r}_1 = \mathbf{x} - \mathbf{c}_1$ to obtain the second IMF $\mathbf{c}_2$. This procedure is repeated on all the subsequent $\mathbf{r}_j$. Then we have

   $$\mathbf{r}_1 - \mathbf{c}_2 = \mathbf{r}_2, \ldots, \mathbf{r}_{m-1} - \mathbf{c}_m = \mathbf{r}_m.$$

7. End the operation when the residue $\mathbf{r}_m$ becomes so small that it is less than a predetermined value or when it becomes a monotonic function therefore cannot be further decomposed.

Thus, after the above EMD process, we have decomposed our data $\mathbf{x}$ into m IMFs $\{\mathbf{c}_i\}_{i=1}^m$ and a residue, $\mathbf{r}_m$. Mathematically, we have,

$$\mathbf{x} = \mathbf{r}_m + \sum_{i=1}^{m} \mathbf{c}_i \tag{1}$$

Since the local mean with low frequency has been iteratively removed from the original data, the first IMF $\mathbf{c}_1$ should represent the highest-frequency component and subsequent IMFs have lower and lower frequency ranges. The residue can either be the mean trend or a constant. For data with a trend, the final residue $\mathbf{r}_m$ should be that trend (Huang *et al.*, 1998).

Since the IMFs and residue, as the output of EMD, have different frequency ranges, the summation of low frequency IMFs with the residue can be considered as the output of passing the original data $\mathbf{x}$ through a low-pass filter, for instance,

$$\mathbf{r}_m + \sum_{i=i_0}^{m} \mathbf{c}_i, \tag{2}$$

where i_0 is close to m is a low-frequency version of $\mathbf{x}$. In particular, the residue term $\mathbf{r}_m$ itself represents the output of $\mathbf{x}$ after filtering out all high-frequency components.

Let the given data $\mathbf{x}$ be the vector consisting of the stock prices in a day, and $\mathbf{r}_m$ is the residual term of $\mathbf{x}$ from EMD. Then the EMD-candlestick is defined to be the open, high, low and close prices of the first, maxima, minima and last values of $\mathbf{r}_m$ respectively. Under this definition, the EMD-candlestick can be considered as the summary of the daily performance of the stock after filtering out the high frequency components, or in other word, the intraday noises. The main purpose of this study is to investigate whether this EMD-candlestick can improve the performance of technical analysis trading rules, when compared with the performance of these rules using the traditional candlestick generated from the same data.

3 Methodology

3.1 Data

In this study, we select the data following Scalas *et al.* (2004) who use securities in the Dow Jones Industrial Average Index (DJIA) in the analysis of waiting time of high-frequency financial data. The data used in this study is retrieved from Wharton Research Data Services (WRDS) through the dataset Trade and Quote (TAQ). We collect TAQ data for the period of 1993 to 2012. We consider all the DJIA securities with complete data during this period. There are 14 securities satisfying this criteria and the codes are: AXP, BA, CAT, DD, DIS, GE, IBM, JPM, KO, MCD, MMM, MRK, PG and UTX. We follow Liu and Maheu (2008) to filter out invalid trades by using correction indicator. The trade data is kept only if the correction indicators equal 0 or 1, which refer to regular trade and later-corrected trades respectively. The traditional candlestick from the original data can be easily obtained by simply taking the price of the first trade as open price, the maximal price of all trade as high price, the minimal price of all trade as low price and the price of the last trade or the official closing price as the close price.

Since EMD algorithm needs regular time series data as input, 1-second data in one day will be used to generate the EMD-candlestick. For each day, the time range of the dataset starts from the time of the first trade to the time of the last trade of the day. For every second in this range, the price of the last trade in this second will be used to form the input of the EMD. If there is no trade in one second, the price of that second will be taken from the previous second. The sequence of prices in one day will be processed by EMD to obtain the residue.

Take the security GE on 22 January 2012 as example. This security was traded in the first second and the last second of the trading session of this day. Since the trading session of New York Stock Exchange is from 9:30 AM to 4:00 PM, with a duration of 23400 seconds, a list of price $\mathbf{x} = (x_1, x_2, \cdots, x_{23400})$ can be formed according to the above rules. Then $\mathbf{x}$ is processed by EMD to obtain IMFs $\mathbf{c}_1, \mathbf{c}_2, \cdots, \mathbf{c}_{13}$, and the final residue $\mathbf{r}$, as illustrated in Figure 1.

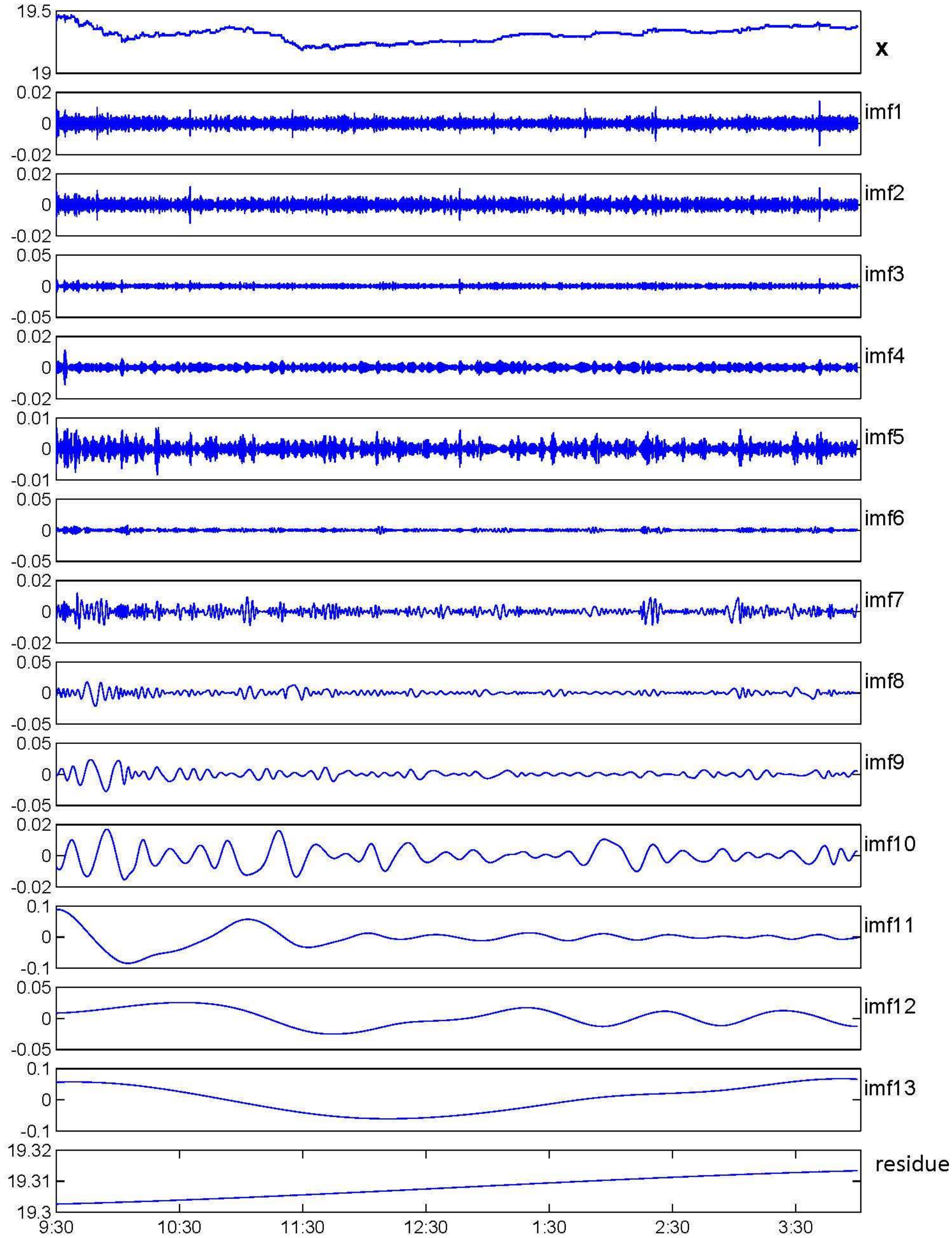

Figure 1: IMF components and residue of 1-second price of GE on 22 January 2012

As shown in Figure 1, the IMFs $\mathbf{c}_1, \mathbf{c}_2, \cdots, \mathbf{c}_{11}$ represents components of $\mathbf{x}$ in different average frequencies and the residue $\mathbf{r}$ represents the trend of the original data by filtering out the high-frequency components. Then the EMD-candlestick of one day can be formed by taking the first, maximal, minimal and the last values of $\mathbf{r}$ as the daily open, high, low and close prices. Table 1 shows the comparison of the traditional candlestick and EMD-candlestick for this example. It can be observed that the value of EMD-candlestick is numerically close to the value of traditional candlestick. However, the trend of the original data $\mathbf{x}$ and the residue $\mathbf{r}$ is different. The open price is larger than the close price for the original data while the open price is less than the close price for EMD-candlestick. This difference may lead to the different results of the trading strategies that use these two kinds of candlestick as input.

	Traditional candlestick	EMD-candlestick
Open	19.42	19.303
High	19.47	19.313
Low	19.18	19.303
Close	18.37	19.313

Table 1: Comparison of the traditional candlestick and EMD-candlestick for GE, 22 January 2012.

Figure 2 shows the series of daily traditional candlesticks and EMD-candlesticks of GE in the year of 2012. It can be observed that the two series have similar trends, but the EMD series shows a clearer price path and has less noise in the intraday level.

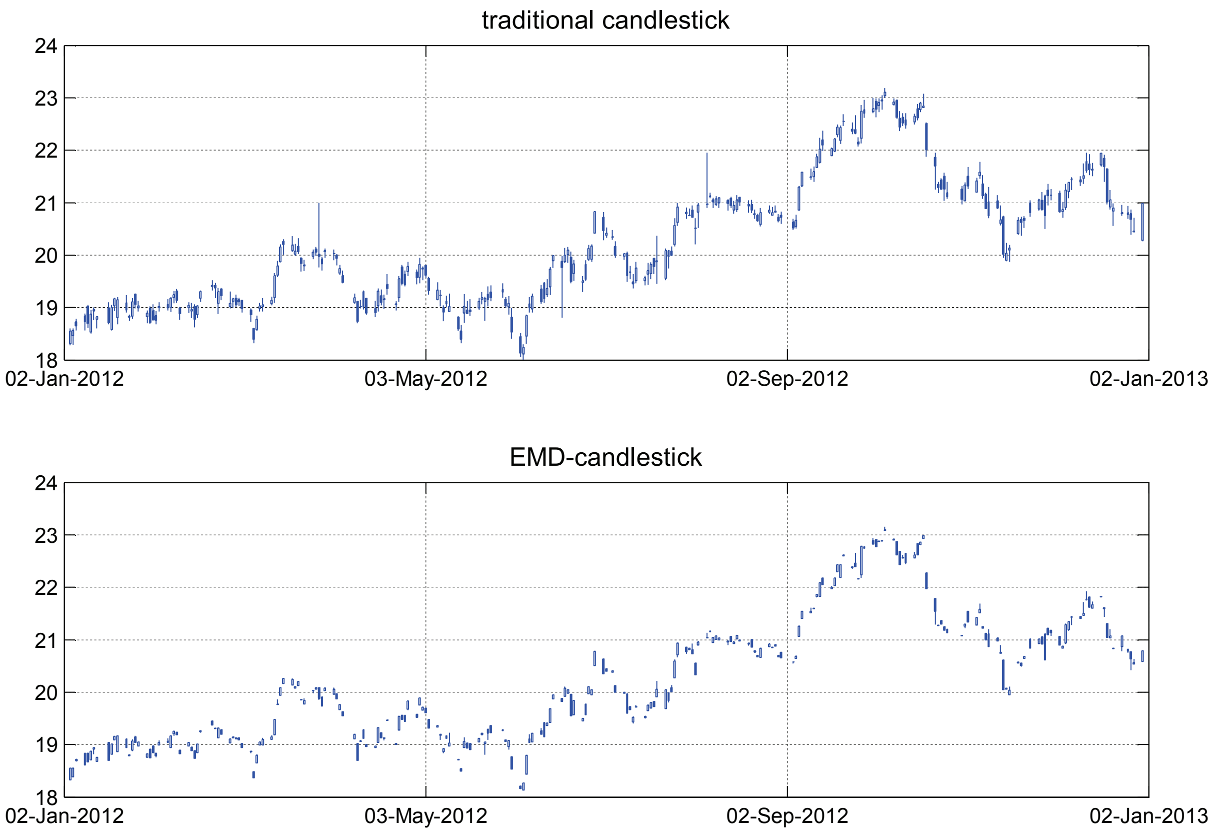

Figure 2: Traditional candlesticks and EMD-candlestick of GE from 4 January 2012 to 31 December 2012

3.2 Trading Rules

To evaluate the quality of the EMD-candlestick methodology, we investigate the impact on the profitability of trading rules available in technical analysis. We select some classes of trading rules which capture different characteristics of the candlestick as input of their trading rules.

Firstly, we follow Brock *et al.* (1992) to evaluate the same set of twenty-six technical trading rules, including ten Variable Length Moving Average (VMA) rules, ten Fixed Length Moving Average (FMA) rules and six Trading Range Break (TRB) rules, with the official closing price and EMD closing price acting as signal generators.

Secondly, we study the relative strength index (RSI) which is a popular indicator proposed by Wilder (1978) showing the strength or weakness in price information. Wong *et al.* (2003) propose a trading strategy on RSI using '50 crossover' rule and investigate its profitability in Singapore stock market. The same set of four RSI rules are evaluated in this paper.

Thirdly, we study trading rules that use not only the close price. Lam *et al.* (2007) propose Intraday and Interday Momentum (IIM) rules, using daily open, high, low and close price as price generators. The same set of 45 IIM rules are evaluated. The detail and the parameters that we examined for each aforementioned strategies are provided in Appendix A.

3.3 Hypothesis testing

For each rule of a certain strategy, we calculate the average daily return (or average 10-day return for FMA and TRB trading rules) of the 14 securities using traditional candlestick and EMD-candlestick as signal generators respectively. Then, we obtain the sample of average returns of the 14 securities using traditional candlestick as price generator, $S = (r_1, r_2, ..., r_{14})$. Similarly, we obtain another sample of average returns of the 14 securities using EMD-candlestick as price generator, $S' = (r'_1, r'_2, ..., r'_{14})$. Let μ_1 and μ_2 denote the average returns of the two samples S and S' respectively. In order to investigate whether the EMD-denoised price can improve the performance of the technical trading strategies, we test the null hypothesis that generating signals using traditional candlestick produces higher returns than using EMD-candlestick, i.e,

$$H_0 : \mu_1 \geq \mu_2 \quad \text{against} \quad H_1 : \mu_1 < \mu_2.$$

Since the returns in the two samples are generated from the same securities, we use paired t-test to compare the means of the two samples. The test statistic is calculated as:

$$t = \frac{\bar{d}}{\sqrt{s^2/n}},$$

where $\bar{d}$ is the mean difference between two samples μ_1 and μ_2, s^2 is the sample variance, n is the sample size and t is a paired sample t-test with $n-1$ degrees of freedom.

4 Empirical results

Table 2 summarizes the results of all strategies in the empirical test. In Table 2, the number of rules that tested for each strategy is presented in the second column. Let μ_1 and μ_2 denote the average daily returns for strategy VMA, RSI and IIM or the average 10-day returns for FMA and TRB, using traditional candlestick and EMD-candlestick as signal generator respectively. Table 2 also shows the average difference $(\mu_2 - \mu_1)$ between the two returns, the percentage of the rules that μ_2 is better, and the percentage of the rules that the result is significant to reject the null hypothesis at five percent. All these three statistics are presented for buy strategy, sell strategy and overall result respectively. We can conclude from the table that VMA, RSI and IIM strategies are more profitable for buy, sell and overall strategies, when EMD-candlestick is used than when traditional candlestick is used.

		Buy strategy			Sell strategy			Overall (B-S)		
Strategy	Total rules	Average Difference (%)	Rules that EMD's return is better	Significant at 5%	Average Difference (%)	Rules that EMD's return is better	Significant at 5%	Average Difference (%)	Rules that EMD's return is better	Significant at 5%
VMA	10	0.0034	100%	70%	-0.0040	90%	40%	0.0036	90%	60%
FMA	10	0.0004	50%	10%	-0.0020	50%	10%	0.0006	50%	10%
TRB	6	-0.0571	50%	0	-0.0179	67.7%	0	-0.0299	50%	0
RSI	4	0.1058	100%	100%	-0.0888	100%	100%	0.0973	100%	100%
IIM	45	0.0356	97.7%	35.5%	-0.0235	84.4%	31.1%	0.0298	100%	44.4%

Table 2: Summary of the empirical results

In Table 3 (see Appendix B), the results for the trading strategies generating signals from the original close prices are presented in column 2, 4, 6, 8, 10 with the number of buy signals, the number of sell signals, mean of the returns from buy signals, mean of the returns from sell signals, and mean of the overall returns from the VMA rules. Similarly, the results for the trading strategies generating signals with EMD closing prices are presented in column 3, 5, 7, 9, 11. The buy return using EMD prices as signal generators is higher and the average of the difference is about 0.0034 percent. Out of the ten tests, all tests show better return using EMD prices and seven test results are significant at five percent level to reject the null hypothesis that the returns of generating signals with traditional candlestick is better than those with the EMD prices using a one-tailed test. For sell returns, the results are similar. Nine tests show better return using EMD prices as signal generators and the average of these difference is -0.0040 percentage. Four tests results are significant at five percent level to reject the null hypothesis. For the overall returns presented in column 10 and 11, the average of these difference is 0.0036 percentage. Six tests result are significant at five percent level.

Tables 4 and 5 show the empirical results for FMA and TRB, respectively. However, for these two strategies, generating signals with EMD-candlestick does not produce a higher return than generating with the traditional candlestick in general. For the overall return of the FMA case, only half of test results show the better return using EMD prices and only one of them is significant at five percent level. For the overall return of the TRB case, only half test results show the better return using EMD prices and none of them is significant at five percent level. For the case that the return from traditional candlestick is better than that from EMD-candlestick, the null hypothesis that generating signals using EMD-candlestick produces higher return than using traditional candlestick is also tested and no result is significant at five percent level.

Table 6 shows the results for RSI trading strategy. Generating signals with EMD-candlestick produces a higher return than generating with the traditional candlestick for all the rules tested. The average of the differences for buy returns, sell returns and overall returns are about 0.1058, -0.0889, and 0.0972 percent respectively. All the results are significant at five percent level to reject the null hypothesis.

Table 7 to Table 9 show the results for IIM trading strategy. Generating signals with EMD-candlestick produces a higher return than generating with the traditional candlestick in general. The average of the differences for buy returns, sell returns and overall returns is about 0.0356, -0.0235, and 0.0298 percent respectively. For the overall return, 20 of total 45 test results are significant at five percent level to reject the null hypothesis and 31 test results are significant at ten percent level.

5 Conclusion

In this paper, we attempt to improve the profitability of technical trading strategies by using the EMD-candlestick instead of the traditional candlestick as signal generator. We empirically test the usefulness of EMD-candlestick on the trading strategies VMA, FMA, TRB, RSI that use close price as signal generator and trading strategy IIM that uses all the information in the daily candlestick as signal generator. The EMD-candlestick significantly improves the performance of the trading strategies VMA, RSI and IIM, and the effect is not significant for the strategies FMA and TRB. In view of the positive empirical results, we propose the broader usage of the EMD-candlestick in financial data analysis as a replacement of the traditional candlestick which could be affected by noise. The methodology of the EMD-candlestick can also be easily applied to other areas of finance. Since we only use the residue term $\mathbf{r}$ in this paper, the effect of using the other IMFs $\{\mathbf{c}_i\}$ will be investigated in future papers.

A Appendix

A.1 Variable Length Moving Average (VMA)

The VMA rules generate a buy (sell) signal when the short moving average is above (below) the long moving average by a margin called 'band'. For a zero band, all days are classified as either buy or sell. For a non-zero band, all days are classified as buy, sell or neutral when no signal is generated. Following Brock *et al.* (1992), the most popular rules, 1-50 (period of short moving average is 1-day and period of long moving average is 50-day), 1-150, 5-150, 1-200, 2-200, are investigated. These rules are also tested with and without a one percent band. Total 10 rules are tested in this paper.

A.2 Fixed Length Moving Average (FMA)

Similarly, the FMA rules generate a buy (sell) signal when the short-term moving average cuts the long-term moving average from below (above). The holding period is a fixed 10-day period as suggested by Brock *et al.* (1992). Returns are recorded at the end of each holding period and all signals occurring during this 10-day period are ignored. The same rules as VMA strategy, 1-50, 1-150, 5-150, 1-200, 2-200, are tested and the rules are also tested with and without a one percent band in this paper. Therefore, total ten rules are tested in this paper.

A.3 Trading Range Break (TRB)

The TRB rules generate a buy (sell) signal when the price rises above (falls below) the resistance (support) level, which is defined as a local maximum (minimum) over n trading days. TRB rules are designed according to the idea that many investors are willing to buy at trough, making the price hard to penetrate the previous trough. When the price falls below the support level, it is expected to further drops and therefore a sell signal is generated. The rationale is vice versa for that of the buy signal and resistance level.

Similar to the FMA rules, the holding period is set to be 10 trading days and any signals during this holding period are ignored. Following (Brock *et al.*, 1992), the number of days n being tested are 50, 150 and 200. These rules are also tested with and without a one percent band. Total six rules are tested in this paper.

A.4 Relative Strength Index (RSI)

The relative strength index strategy using '50 crossover' trading rule is proposed by Wong *et al.* (2003). Let C_t be the daily close price at time t. Then we can define

$$U_i = \begin{cases} C_i - C_{i-1} & \text{if } C_i > C_{i-1} \\ 0 & \text{otherwise,} \end{cases}$$

$$D_i = \begin{cases} C_{i-1} - C_i & \text{if } C_i < C_{i-1} \\ 0 & \text{otherwise.} \end{cases}$$

The next step is to define

$$U_N(t) = \frac{\sum_{t-N+1}^{t} U_i}{N},$$

$$D_N(t) = \frac{\sum_{t-N+1}^{t} D_i}{N},$$

$$RS_N(t) = \frac{U_N(t)}{D_N(t)}.$$

The RSI at time t is then defined as

$$RSI_N(t) = 100 - \frac{100}{1 + RS_N(t)}.$$

The '50 crossover' method generates a buy signal when the RSI rises above 50 and a sell signal when the RSI falls below 50. The same four rules tested by Wong *et al.* (2003), which let N equals to 5, 10, 20, 30 respectively, are tested in this paper.

A.5 Intraday and Interday Momentum (IIM)

The IIM strategies, based on the Japanese Candlesticks concepts, are proposed by Lam *et al.* (2007). Let O_t, H_t, L_t, C_t be the daily open, high, low and close price at time t. We first define the N-day Average Intraday Momentum (AIM) at t as follows,

$$AIM_N(t) = \frac{\sum_{t-N+1}^{t} |C_i - O_i|}{N}. \tag{3}$$

Then we define the N-day Average Interday Momentum (AOM) at t as follows,

$$AOM_N(t) = \frac{\sum_{t-N+1}^{t} |C_i - C_{i-1}|}{N}. \tag{4}$$

Five trading rules can be designed as follows,

Rule 1 Buy:

$$C_t - O_t > AIM_N(t) \times k, \tag{5}$$

Sell:

$$O_t - C_t > AIM_N(t) \times k. \tag{6}$$

Rule 2 Buy:

$$(8) \ \textbf{and} \ \ C_t - O_t > H_t - C_t + O_t - L_t, \tag{7}$$

Sell:

$$(9) \ \textbf{and} \ \ O_t - C_t > H_t - O_t + C_t - L_t. \tag{8}$$

Rule 3 Buy:

$$C_t - C_{t-1} > AOM_N(t) \times k, \tag{9}$$

Sell:

$$C_{t-1} - C_t > AOM_N(t) \times k. \tag{10}$$

Rule 4 Buy: when (8) **or** (12)

Sell: when (9) **or** (13)

Rule 5 Buy: when (8) **and** (12)

Sell: when (9) **and** (13)

For the parameter k, the values 1, 1.5 and 2 are examined. For the parameter N, which represents the days used to calculate AIM and AOM, the values 10, 20, 50 are examined. Let the rule number above be a parameter, then we can form the set of parameters, (rule number, k, N). For example, $(1, 1.5, 20)$ represents the strategy that generates signals with rule 1, $k = 1.5$ and $N = 20$. Totally $5 \times 3 \times 3 = 45$ parameter sets are tested in this paper.

B Appendix

Table 3: Comparison of generating with EMD-candlestick and traditional candlestick for VMA

test	N(buy)	N(buy)*	N(sell)	N(sell)*	buy	buy*	sell	sell*	overall	overall*
(1,50,0)	39870	39915	29691	29651	-0.0185	-0.0099	0.0335	0.0213	-0.0245	-0.0144
					(0.0025)		**(0.0036)**		**(0.0029)**	
(1,50,0.01)	35034	35088	25316	25286	-0.0207	-0.0126	0.0406	0.0358	-0.0284	-0.0217
					(0.0051)		(0.1538)		**(0.0070)**	
(1,150,0)	40656	40689	27507	27477	-0.0156	-0.0105	0.0305	0.0230	-0.0209	-0.0149
					(0.0008)		**(0.0015)**		**(0.0010)**	
(1,150,0.01)	38259	38294	25123	25115	-0.0175	-0.0150	0.0348	0.0314	-0.0236	-0.0208
					(0.0239)		(0.0790)		**(0.0170)**	
(5,150,0)	40629	40691	27536	27475	-0.0105	-0.0084	0.0238	0.0207	-0.0152	-0.0127
					(0.0229)		**(0.0235)**		**(0.0229)**	
(5,150,0.01)	38121	38149	25059	25064	-0.0105	-0.0103	0.0280	0.0247	-0.0165	-0.0152
					(0.4249)		**(0.0118)**		(0.0626)	
(1,200,0)	40734	40751	26732	26715	-0.0134	-0.0117	0.0273	0.0245	-0.0179	-0.0159
					(0.1390)		(0.1243)		(0.1326)	
(1,200,0.01)	38712	38758	24849	24805	-0.0174	-0.0140	0.0284	0.0264	-0.0210	-0.0182
					(0.0019)		(0.1742)		**(0.0133)**	
(2,200,0)	40781	40786	26684	26680	-0.0158	-0.0156	0.0309	0.0313	-0.0208	-0.0208
					(0.4594)		(0.4645)		(0.4944)	
(2,200,0.01)	38703	38737	24817	24770	-0.0169	-0.0148	0.0346	0.0333	-0.0227	-0.0211
					(0.0376)		(0.2584)		**(0.0366)**	

Notes: The sample period is from January 1993 to December 2012. Those columns with (without) * are the results for VMA rules with close price in EMD candlestick (the original close price) as the signal generator. N(Buy) and N(Sell) are the numbers of buy and sell signals reported in the sample. All returns are calculated in logarithm and reported in percentage level. The numbers in the parentheses below are the t-ratios. They test the null hypothesis that $\mu_1 \geq \mu_2$. The t-ratios that are less than the five percent significance level are highlighted in bold face.

Table 4: Comparison of generating with EMD-candlestick and traditional candlestick for FMA

test	N(buy)	N(buy)*	N(sell)	N(sell)*	buy	buy*	sell	sell*	overall	overall*
(1,50,0)	3966	3969	2981	2978	-0.0806	-0.0619	0.1953	0.1721	-0.1273	-0.1069
					(0.1798)		(0.1952)		(0.1877)	
(1,50,0.01)	3868	3880	2884	2873	-0.1416	-0.1836	0.2879	0.3111	-0.2012	-0.2357
					(0.1376)		(0.3539)		(0.2261)	
(1,150,0)	4068	4065	2739	2742	-0.1315	-0.1317	0.2784	0.2816	-0.1851	-0.1862
					(0.4905)		(0.3827)		(0.4519)	
(1,150,0.01)	4019	4022	2688	2689	-0.0783	-0.0905	0.1958	0.2486	-0.1183	-0.1473
					(0.3680)		(0.1594)		(0.2425)	
(5,150,0)	4049	4056	2758	2751	-0.1215	-0.1201	0.2680	0.2656	-0.1737	-0.1716
					(0.3969)		(0.3789)		(0.3706)	
(5,150,0.01)	3976	3993	2660	2640	-0.1228	-0.1203	0.2875	0.2580	-0.1821	-0.1696
					(0.4251)		(0.1203)		(0.2206)	
(1,200,0)	4064	4059	2673	2678	-0.1471	-0.1429	0.3057	0.2953	-0.2007	-0.1946
					(0.3709)		(0.3204)		(0.3520)	
(1,200,0.01)	4032	4025	2624	2626	-0.1727	-0.1266	0.3124	0.2564	-0.2176	-0.1679
					(0.0168)		**(0.0195)**		**(0.0146)**	
(2,200,0)	4063	4065	2674	2672	-0.1353	-0.1445	0.2838	0.2997	-0.1855	-0.1967
					(0.1920)		(0.1456)		(0.1785)	
(2,200,0.01)	4011	4003	2623	2629	-0.1297	-0.1347	0.2828	0.2889	-0.1768	-0.1854
					(0.3745)		(0.4221)		(0.3362)	

Notes: The sample period is from January 1993 to December 2012. Those columns with (without) * are the results for FMA rules with close price in EMD-candlestick (the original close price) as the signal generator. N(Buy) and N(Sell) are the numbers of buy and sell signals reported in the sample. All returns are average 10-day return, which are calculated in logarithm and reported in percentage level. The numbers in the parentheses below are the t-ratios. They test the null hypothesis that $\mu_1 \geq \mu_2$. The t-ratios that are less than the five percent significance level are highlighted in bold face.

Table 5: Comparison of generating with EMD-candlestick and traditional candlestick for TRB

test	N(buy)	N(buy)*	N(sell)	N(sell)*	buy	buy*	sell	sell*	overall	overall*
(1,50,0)	1846	1125	1859	1156	-0.3219	-0.2960	0.3804	0.3666	-0.3489	-0.3250
					(0.2627)		(0.4057)		(0.2694)	
(1,50,0.01)	1217	1242	846	845	-0.3848	-0.5778	0.6205	0.5172	-0.4836	-0.5581
					(0.1026)		(0.3035)		(0.3067)	
(1,150,0)	1198	1197	509	528	-0.2880	-0.2164	0.4647	0.3913	-0.3577	-0.2924
					(0.0603)		(0.3825)		(0.2213)	
(1,150,0.01)	783	798	409	402	-0.4855	-0.6182	0.8072	0.9985	-0.6281	-0.7636
					(0.2707)		(0.2947)		(0.2808)	
(1,200,0)	1078	1069	412	427	-0.3321	-0.2663	0.4772	0.3702	-0.3903	-0.3256
					(0.1171)		(0.3354)		(0.2168)	
(1,200,0.01)	693	704	334	331	-0.5539	-0.7183	0.6845	0.9826	-0.6500	-0.8318
					(0.2643)		(0.2288)		(0.2507)	

Notes: The sample period is from January 1993 to December 2012. Those columns with (without) * are the results for TRB rules with close price in EMD-candlestick (the original close price) as the signal generator. N(Buy) and N(Sell) are the numbers of buy and sell signals reported in the sample. All returns are average 10-day return, which are calculated in logarithm and reported in percentage level. The numbers in the parentheses below are the t-ratios. They test the null hypothesis that $\mu_1 \geq \mu_2$. The t-ratios that are less than the five percent significance level are highlighted in bold face.

Table 6: Comparison of generating with EMD-candlestick and traditional candlestick for RSI

test	N(buy)	N(buy)*	N(sell)	N(sell)*	buy	buy*	sell	sell*	overall	overall*
5	7264	7312	7268	7297	1.4469	1.5455	-1.4456	-1.5488	1.4462	1.5471
					(0.0000)		**(0.0000)**		**(0.0000)**	
10	4991	5078	4989	5064	1.3847	1.4800	-1.5538	-1.6127	1.4693	1.5463
					(0.0000)		**(0.0295)**		**(0.0001)**	
20	3450	3514	3449	3493	1.3810	1.5096	-1.7007	-1.7851	1.5408	1.6478
					(0.0000)		**(0.0013)**		**(0.0000)**	
30	2765	2847	2757	2814	1.4008	1.5015	-1.8503	-1.9590	1.6252	1.7292
					(0.0004)		**(0.0002)**		**(0.0000)**	

Notes: The sample period is from January 1993 to December 2012. Those columns with (without) * are the results for RSI rules with close price in EMD-candlestick (the original close price) as the signal generator. N(Buy) and N(Sell) are the numbers of buy and sell signals reported in the sample. All returns are average daily return, which are calculated in logarithm and reported in percentage level. The numbers in the parentheses below are the t-ratios. They test the null hypothesis that $\mu_1 \geq \mu_2$. The t-ratios that are less than the five percent significance level are highlighted in bold face.

Table 7: Comparison of generating with EMD-candlestick and traditional candlestick for IIM

test	N(buy)	N(buy)*	N(sell)	N(sell)*	buy	buy*	sell	sell*	overall	overall*
(1,10,1)	15332	14636	14336	13949	-0.0260	-0.0189	0.0367	-0.0012	-0.0306	-0.0087
					(0.3340)		**(0.0397)**		(0.0878)	
(1,10,1.5)	8303	8372	7447	7707	-0.0443	-0.0200	0.0106	-0.0019	-0.0276	-0.0093
					(0.1909)		(0.3136)		(0.1597)	
(1,10,2)	4020	4529	3443	3892	-0.1040	0.0371	-0.0489	-0.0159	-0.0301	0.0289
					(0.0147)		(0.2223)		(0.0778)	
(1,20,1)	15034	14315	14082	13554	-0.0437	-0.0295	0.0373	0.0013	-0.0400	-0.0154
					(0.1920)		**(0.0456)**		(0.0763)	
(1,20,1.5)	8337	8298	7389	7560	-0.0473	-0.0232	0.0274	0.0011	-0.0370	-0.0124
					(0.1316)		(0.1424)		(0.0827)	
(1,20,2)	4255	4620	3586	4027	-0.0445	0.0349	-0.0174	0.0171	-0.0148	0.0117
					(0.0343)		(0.2021)		(0.2130)	
(1,50,1)	14673	14047	13785	13192	-0.0472	-0.0220	0.0409	0.0043	-0.0433	-0.0132
					(0.0915)		**(0.0245)**		**(0.0433)**	
(1,50,1.5)	8312	8232	7290	7400	-0.0283	-0.0321	0.0251	-0.0119	-0.0256	-0.0105
					(0.4458)		(0.1590)		(0.2373)	
(1,50,2)	4364	4659	3634	4015	-0.0375	0.0018	0.0512	0.0043	-0.0433	-0.0002
					(0.1436)		(0.0944)		(0.0864)	
(2,10,1)	12811	14403	11717	13699	-0.0449	-0.0189	0.0524	0.0072	-0.0478	-0.0126
					(0.0984)		**(0.0302)**		**(0.0313)**	
(2,10,1.5)	7743	8323	6809	7647	-0.0537	-0.0187	0.0267	0.0096	-0.0404	-0.0140
					(0.1375)		(0.2724)		(0.0914)	
(2,10,2)	3882	4517	3301	3877	-0.1130	0.0390	-0.0239	-0.0131	-0.0476	0.0287
					(0.0116)		(0.4076)		**(0.0441)**	
(2,20,1)	12807	14122	11731	13364	-0.0522	-0.0289	0.0568	0.0088	-0.0538	-0.0186
					(0.1064)		**(0.0199)**		**(0.0348)**	
(2,20,1.5)	7857	8268	6881	7518	-0.0640	-0.0224	0.0493	0.0007	-0.0566	-0.0118
					(0.0466)		**(0.0410)**		**(0.0076)**	
(2,20,2)	4135	4613	3463	4017	-0.0588	0.0336	0.0092	0.0185	-0.0349	0.0103
					(0.0173)		(0.4078)		(0.0904)	

Table 8: Comparison of generating with EMD-candlestick and traditional candlestick for IIM (cont.)

test	N(buy)	N(buy)*	N(sell)	N(sell)*	buy	buy*	sell	sell*	overall	overall*
(2,50,1)	12640	13862	11573	13006	-0.0523	-0.0239	0.0545	0.0121	-0.0526	-0.0178
					(0.0895)		**(0.0244)**		**(0.0344)**	
(2,50,1.5)	7849	8205	6822	7359	-0.0457	-0.0327	0.0469	0.0018	-0.0453	-0.0173
					(0.3461)		(0.1149)		(0.1023)	
(2,50,2)	4252	4651	3508	4003	-0.0517	0.0019	0.0745	0.0071	-0.0621	-0.0015
					(0.0692)		**(0.0450)**		**(0.0291)**	
(3,10,1)	15277	15206	14145	14087	0.0089	0.0188	0.0400	0.0431	-0.0144	-0.0107
					(0.1698)		(0.3859)		(0.3159)	
(3,10,1.5)	8416	8504	7212	7290	-0.0072	0.0176	0.0445	0.0255	-0.0243	-0.0021
					(0.0285)		(0.0543)		**(0.0125)**	
(3,10,2)	4120	4290	3277	3417	-0.0038	0.0308	0.0678	0.0146	-0.0320	0.0114
					(0.0123)		**(0.0076)**		**(0.0009)**	
(3,20,1)	14956	14868	13716	13654	0.0044	0.0168	0.0461	0.0374	-0.0195	-0.0091
					(0.0755)		(0.2262)		(0.0981)	
(3,20,1.5)	8335	8292	7154	7181	-0.0128	0.0170	0.0461	0.0279	-0.0280	-0.0037
					(0.0476)		(0.0985)		**(0.0213)**	
(3,20,2)	4270	4386	3475	3484	0.0047	0.0269	0.0907	0.0491	-0.0377	-0.0060
					(0.0960)		**(0.0404)**		**(0.0104)**	
(3,50,1)	14574	14433	13399	13197	-0.0073	0.0055	0.0395	0.0237	-0.0225	-0.0083
					(0.1332)		(0.0778)		(0.0712)	
(3,50,1.5)	8165	8216	7052	7023	-0.0338	0.0081	0.0579	0.0199	-0.0446	-0.0046
					(0.0024)		(0.0590)		**(0.0015)**	
(3,50,2)	4338	4388	3523	3611	-0.0426	-0.0159	0.0762	0.0677	-0.0577	-0.0395
					(0.1954)		(0.3726)		(0.2149)	
(4,10,1)	19310	20436	18090	19001	-0.0219	-0.0082	0.0234	0.0049	-0.0225	-0.0064
					(0.1620)		(0.1107)		(0.1053)	
(4,10,1.5)	11126	12215	9975	11006	-0.0404	-0.0161	-0.0089	-0.0089	-0.0167	-0.0040
					(0.0832)		(0.4995)		(0.1248)	
(4,10,2)	5762	6742	4869	5715	-0.0833	0.0209	-0.0435	-0.0171	-0.0244	0.0201
					(0.0108)		(0.1053)		**(0.0435)**	
(4,20,1)	18816	19883	17625	18516	-0.0311	-0.0099	0.0241	0.0018	-0.0276	-0.0059
					(0.0408)		(0.0790)		**(0.0487)**	

Table 9: Comparison of generating with EMD-candlestick and traditional candlestick for IIM (cont.)

test	N(buy)	N(buy)*	N(sell)	N(sell)*	buy	buy*	sell	sell*	overall	overall*
(4,20,1.5)	11000	11896	9752	10772	-0.0506	-0.0166	0.0119	-0.0068	-0.0322	-0.0053
					(0.0271)		(0.1324)		**(0.0122)**	
(4,20,2)	5852	6722	4938	5768	-0.0364	0.0220	-0.0244	0.0058	-0.0085	0.0092
					(0.0331)		(0.1555)		(0.1879)	
(4,50,1)	18318	19357	17174	17930	-0.0369	-0.0116	0.0229	0.0077	-0.0297	-0.0097
					(0.0492)		(0.1421)		(0.0676)	
(4,50,1.5)	10767	11738	9569	10451	-0.0386	-0.0177	0.0179	-0.0200	-0.0284	0.0003
					(0.1380)		(0.0883)		**(0.0303)**	
(4,50,2)	5937	6742	4930	5767	-0.0496	-0.0137	0.0187	0.0031	-0.0361	-0.0088
					(0.0717)		(0.2910)		(0.0981)	
(5,10,1)	11299	9406	10168	8601	0.0137	0.0189	0.0655	0.0551	-0.0235	-0.0165
					(0.3528)		(0.3074)		(0.2323)	
(5,10,1.5)	5593	4661	4633	3905	0.0037	0.0393	0.1086	0.0731	-0.0466	-0.0122
					(0.0947)		**(0.0158)**		**(0.0186)**	
(5,10,2)	2378	2077	1835	1565	0.0192	0.0766	0.1451	0.0602	-0.0498	0.0186
					(0.0373)		**(0.0369)**		**(0.0154)**	
(5,20,1)	11174	9300	9971	8346	-0.0008	0.0032	0.0735	0.0555	-0.0350	-0.0247
					(0.3687)		(0.1617)		(0.1049)	
(5,20,1.5)	5672	4694	4734	3893	0.0095	0.0320	0.0885	0.0753	-0.0348	-0.0172
					(0.1836)		(0.2695)		(0.1370)	
(5,20,2)	2673	2284	2099	1718	0.0164	0.0584	0.1872	0.1226	-0.0707	-0.0184
					(0.0466)		**(0.0138)**		**(0.0100)**	
(5,50,1)	10929	9123	9815	8102	-0.0110	-0.0000	0.0709	0.0305	-0.0390	-0.0142
					(0.3033)		**(0.0115)**		**(0.0453)**	
(5,50,1.5)	5710	4710	4714	3884	-0.0183	0.0031	0.0849	0.0653	-0.0480	-0.0270
					(0.1544)		(0.3294)		(0.1444)	
(5,50,2)	2765	2305	2205	1829	-0.0182	0.0133	0.1752	0.1352	-0.0856	-0.0531
					(0.2710)		(0.1637)		(0.1731)	

Notes: The sample period is from January 1993 to December 2012. Those columns with (without) * are the results for IIM rules with EMD candlestick (the traditional candlestick) as the signal generator. N(Buy) and N(Sell) are the numbers of buy and sell signals reported in the sample. All returns are calculated in logarithm and reported in percentage level. The numbers in the parentheses below are the t-ratios. They test the null hypothesis that $\mu_1 \geq \mu_2$. The t-ratios that are less than the five percent significance level are highlighted in bold facex.

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