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Does Moving Average Technical Trading Rule Provide Value for Intraday Stock Trading?: Evidence from the Indonesia Stock Exchange

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This paper analyzes the value of employing simple moving average (SMA) and moving average (MA) technical trading rules for intraday stock trading in the Indonesia Stock Exchange. We test independently SMA[5], SMA[10], SMA[15], MA[5,50], MA[5,150], and MA[5,200] trading rules. We find all three SMAs and MA[5,200] tend to deliver returns greater than the unconditional basic return (UBR), while MA[5,50] and MA[5,150] generate returns less than UBR. We conclude that SMAs are more valuable than MAs as intraday technical trading rules.

Keywords: *Moving average, technical trading rules, intraday stock trading, Indonesia Stock Exchange*

Introduction

Technical analysis is a methodology to forecast future direction of prices through the study of historical market data. Although the analysis primarily utilizes price and volume data, there are several rules of technical analysis commonly used by market participants. Amongst them are relative strength index, moving averages, regressions, inter-market and intra-market price correlations, cycles, and the classic chart patterns.

In reality, most market participants in foreign exchange markets and stock markets place more emphasis on technical analysis in their investments decisions (Gehrig and Menkhoff, 2006), especially the ones with shorter time horizon (Marshall et al., 2006; Oberlechner, 2001). However, most finance academia still view technical analysis to be in clash with Efficient Market Hypotheses (EMH) as one of the central pillars of finance.

Despite all extant academic debates, the main issue in this paper is whether technical trading rule is a valuable trading strategy. Previous studies over the profitability of technical analysis have yielded conflicting results. The study of Allen and Karjalainen (1999) reveals that after considering transaction costs, technical trading rules based on genetic algorithm

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do not earn excess return over buy and hold strategy. Similarly, after applying two bootstrap methodologies and considering data snooping bias in intraday context, Marshall, Cahan, and Cahan (MCC) (2006), find that none of the 7,846 popular technical trading rules tested are profitable.

On the contrary, Brock, Lakonishok, and Lebaron (BLL) (1992) find buy signals consistently generate higher returns over sells signals, through the application of moving average and trading range break rules to the Dow Jones Industrial Average. Applying BLL methodology to the Jakarta Composite Index, Fuadi (2007) also finds that moving average rules can generate greater return than buy and hold strategy. Furthermore, Sullivan et al. (1999) confirm that BLL study is robust to data-snooping bias, and even suspect that there are technical trading rules more profitable than the ones considered by BLL.

This paper attempts to contribute in at least three ways. *Firstly*, studies assessing the value of technical analysis still yield conflicting results. This study is expected to enrich the existing body of knowledge. *Secondly*, most studies are conducted in developed markets. To the best of our knowledge, the only study in Indonesia stock market, as one of the emerging markets, is conducted by Fuadi (2007). This study, however, only compares returns from moving average rules and buy and hold strategy. It does not compare returns from moving average rules and the unconditional basic return of the series. Furthermore, it does not consider intraday technical analysis, which we think is crucial to short term traders. *Thirdly*, this study is investigating trading rules in intraday context. Intraday trade outcomes are greatly affected by the market microstructure. Although MCC have conducted intraday technical analysis in the US, this study is still relevant since Indonesia Stock Exchange (IDX) has a peculiar market microstructure (Commerton-Forde and Rydge, 2006).

The main objective of this study is to analyze whether moving average technical trading rules can be utilized as valuable intraday trading strategies. We limit our analysis on moving average trading rules, since they are the simplest and widely used form of technical analysis. In this study, we follow MCC value diagnostic of technical trading rules.

The rest of the paper will be organized as follows. The second section will discuss relevant literature, the third section will explain the data and methodology employed in this research, and the last section will offer some conclusions and further research avenues.

Literature Review

By definition, technical analysts will only use data from the market because the market is the best predictor. They also believe that changes in current price may predict forthcoming fundamental changes, even before fundamental analysts are able to detect the changes.

For technical analysts to aptly use historical data to predict future behavior of the market, they must adhere to several assumptions (Levy, 1966). These assumptions are: 1) observed market value (price) of securities is solely driven by the interaction of its supply and demand; 2) the supply and demand in the market are governed by rational and irrational factors, including economic factors as well as mood, opinions, and guesses; 3) individual securities prices and the whole market tend to follow a specific trend, which is likely to persist for some period of time; 4) the trend will change as a reaction to any shifts in supply and demand relationships.

Technical analysis has always triggered academic debates. The center of the debate comes from Efficient Market Hypotheses (EMH) (Fama, 1970). If traders can generate superior risk-adjusted return using technical trading rules, then the market is slow to adjust to new pertinent information. In EMH term, the market is inefficient. However, many studies support the weak-form EMH and find that prices do not move in trend.

Reilly and Brown (2006, pp. 585) argue that technical analysis may quickly predict future prices and returns, but it lacks theorem to support its predictions. On the contrary, fundamental analysis is well grounded in weak-form EMH, but extraordinary return can only be reaped by analyst obtaining and processing

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Table 1. Stocks included in the sample

The stocks are presented as top five, middle five, and bottom five stocks in terms of trading value in 2009.

Stock code	Company name
BUMI	Bumi Resources, Tbk.
TLKM	Telekomunikasi Indonesia, Tbk.
ADRO	Adaro Energy, Tbk.
ASII	Astra Internasional, Tbk.
BBRI	Bank Rakyat Indonesia, Tbk.
TRUB	Truba Alam Manunggal Engineering, Tbk.
BDMN	Bank Danamon, Tbk.
ITMG	Indo Tambangraya Megah, Tbk.
BBNI	Bank Negara Indonesia, Tbk.
MIRA	Mitra International Resources, Tbk.
SGRO	Sampoerna Agro, Tbk.
ELSA	Elnusa, Tbk.
INKP	Indah Kiat Pulp and Paper, Tbk
CTRA	Ciputra Development Tbk
CTRP	Ciputra Properti, Tbk.

new and material information ahead of any other market participant.

Another argument against technical trading rule states that, the application of technical analysis relies a great deal on subjective judgments. For some specified patterns, two technical analysts may arrive at different investment decisions. Furthermore, the success of a particular trading rule will encourage other market participants to adopt that trading rule, and the resulting competition will neutralize the technique.

In spite of all existing academic debates, most market participants in foreign exchange markets and stock markets, rely their investments decisions more on technical analysis, particularly the ones with shorter time horizon (Gehrig and Menkhoff, 2006; Marshall et al., 2006; Oberlechner, 2001).

The main issue in this paper is whether technical trading rules can be applied as viable trading strategies. Previous studies over the profitability of technical analysis still generate inconclusive results. The study of Allen and Karjalainen (1999) and Marshall et al. (2006) do not find any technical trading rule that is profitable. On the contrary, Brock et al. (1992); Fuadi (2007); and Sullivan et al. (1999) support the existence of valuable technical trading rules that yield returns higher than buy and hold strategy.

Despite conflicting results, we hypothesize that SMA and MA trading rules are valuable. Hence, applying them will generate higher return than the unconditional basic return.

Research Method

Data and observation period

To be included in our sample, a stock must always be traded in the IDX and does not experience any split or reverse-split between January 5th, 2009 and December 30th, 2009. We choose year 2009 assuming that subprime crisis is no longer affecting IDX. To avoid severe non-trading problems in our intraday data, we deliberately select the top fifty stocks in terms of trading value. From these 50 stocks, we then pick top five, middle five, and bottom five stocks from the list. Hence, we end up with 15 stocks as our sample (Table 1).

In their study using US stocks, MCC choose five minute intraday observation interval. For IDX active stocks, the average optimal sampling frequency to estimate realized variance is nine minutes (Henker and Husodo, 2010). Therefore, different from MCC, we opt for 10 minute intraday observation interval. The intraday data is collected from the Indonesia Stock Exchange database.

Moving average technical trading rules

The concept of moving average is firstly introduced by Gartley (1935). Moving average is

t	1	2	3	4	5	6	7	8	9	10	
Price	100	100	110	115	115	110	105	105	105	110	
UBR		0.00%	9.53%	4.45%	0.00%	-4.45%	-4.65%	0.00%	0.00%	4.65%	1.06%
											AVG

Figure 1. Illustration of return calculations

Table 2. Descriptive statistics of unconditional basic return (UBR) of each stock in the sample

Unconditional basic return (UBR) is log return ($UBR_t = lnP_t/P_{t-1}$) calculated every 10 minutes. Every stock in the sample generates 7,590 stock return observations.

	Mean	Maximum	Minimum	Skewness	Standard deviation	Kurtosis
BUMI	0.00017	0.0952	-0.1000	-0.3263	0.0105	14.8586
TLKM	0.00005	0.0457	-0.0506	0.3951	0.0052	9.0744
ADRO	0.00019	0.0682	-0.0729	0.7177	0.0079	9.4046
ASII	0.00016	0.0603	-0.0493	0.9580	0.0056	16.5090
BBRI	0.00008	0.0794	-0.0548	0.6636	0.0066	11.6646
TRUB	0.00017	0.1653	-0.2169	0.9235	0.0103	69.2855
BDMN	0.00007	0.0787	-0.2320	-3.6911	0.0075	132.1431
ITMG	0.00015	0.0636	-0.0750	-0.0740	0.0061	17.9379
BBNI	0.00015	0.0667	-0.0476	0.4764	0.0069	5.9221
MIRA	-0.00002	0.0588	-0.1061	-0.0129	0.0089	8.3330
SGRO	0.00013	0.0595	-0.0682	0.4656	0.0071	10.5082
ELSA	0.00018	0.1270	-0.0952	0.9236	0.0097	15.4215
INKP	0.00013	0.1064	-0.0759	1.3548	0.0074	22.9421
CTRA	0.00017	0.0833	-0.0649	0.7122	0.0101	7.1717
CTRP	0.00013	0.0850	-0.1543	-0.1034	0.0096	20.6029

basically a series of averages of different subsets from the full data set. Using fixed subset size, moving average values can be obtained by calculating the average of the first subset, and then roll to the next observations to compute the average of the next subsets. This process is repeated until all data set is covered. Thus, a moving average is not a single value, but series of averages generated from all of the subsets.

Gartley's concept of moving average is now referred as simple moving average (SMA). In practice, SMA tends to be combined between longer and shorter sizes (different *n*). For example, we may combine SMA[50] and SMA[150], or SMA[50] and SMA[200]. The term moving average (MA) represents a combination of SMAs. So, MA[50,150] represents the combination of SMA[50] and SMA[150]. Usually, a buy (sell) signal is generated when shorter moving average trend line crosses longer moving average trend line from below (above).

Return calculations

In this study returns are calculated as log returns. Unconditional basic return (UBR) is raw log return calculated before we apply any technical trading rule. Figure 1 illustrates the calculation of UBR if we observe price series in ten periods (t=10). AVG denotes average return over the ten periods.

When we employ technical trading rules, there will be several buy and sell signals generated. In our illustration, buy signals are most likely to occur in t=2 and t=9, since there are price increases after these two periods. If buy signals do occur in these periods, then they are valuable signals. On the contrary, sell signal is supposed to occur in t=5 because in t=6 the price will decrease.

From this generated signals we then calculate the potential returns. If buy signals do occur in t=2 and t=9, the potential returns are 9.53% and 4.65% respectively. Meanwhile, if the technical trading rule generates sell signals instead of buy signals in t=2 and t=9, then we calculate the realized return assuming we own the stocks since one period before. So in this case the returns are zero for both sell signals in t=2 and t=9. Similar but opposite return calculation technique is applicable for t=5 and t=6.

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Table 3. Summary of returns generated from buy signals (RGBS)

This table presents the mean of returns generated from buy signals (RGBS) after employing SMA[5], SMA[10], SMA[15], MA[5,50], MA[5,150], and MA[5,200] technical trading rules.

	SMA[5]	SMA[10]	SMA[15]	MA[5,50]	MA[5,150]	MA[5,200]
BUMI	0.002423	0.001943	0.001177	-0.000083	-0.000014	0.000048
TLKM	0.001215	0.001034	0.000648	-0.000039	-0.000023	-0.000117
ADRO	0.001879	0.001488	0.001014	-0.000037	-0.000017	-0.000033
ASII	0.001212	0.000934	0.000765	-0.000013	0.000006	0.000143
BBRI	0.001549	0.001251	0.000824	-0.000039	-0.000007	-0.000084
TRUB	0.001688	0.001291	0.000924	0.000010	-0.000016	0.000209
BDMN	0.001542	0.001216	0.000900	-0.000021	-0.000015	-0.000088
ITMG	0.001256	0.000994	0.000838	0.000001	-0.000014	0.000014
BBNI	0.001660	0.001372	0.000923	-0.000040	-0.000013	-0.000002
MIRA	0.001894	0.001555	0.001030	-0.000058	-0.000056	-0.000016
SGRO	0.001615	0.001315	0.000975	-0.000021	-0.000013	-0.000024
ELSA	0.002317	0.001991	0.001267	-0.000077	-0.000035	-0.000010
INKP	0.001460	0.001160	0.000923	-0.000017	-0.000012	0.000068
CTRA	0.002217	0.001852	0.001427	-0.000037	-0.000028	0.000160
CTRP	0.002084	0.001762	0.001309	-0.000188	-0.000176	0.000186
Overall	0.001734	0.001428	0.000996	-0.000044	-0.000029	0.000030

Result and Discussion

Unconditional basic return (UBR)

The unconditional basic return (UBR) is basically log return calculated from time series data for every period of 10 minutes. Therefore, every stock in our sample will generate 7,590 stock return observations.

From Table 1 and Table 2 we learn that all stocks but MIRA generates positive mean return albeit very small. Surprisingly, during the observation period all stocks experience extreme return jumps and drops. For example TRUB at one point in time experiences 16.53% return jump, but also experiences 21.69% drop. These extreme jumps and drops lead to high coefficient of variations. We suspect the extreme return volatility happens during the early period of 2009 where the subprime crisis still affects global capital markets.

Besides high volatility, all stock returns also exhibit high Kurtosis or fat-tailed (leptokurtic) distributions. Some stock returns are positively skewed while others are negatively skewed. INKP exhibits the highest positive Skewness while BDMN exhibits the most negative Skewness and also the highest Kurtosis of 132.14.

Returns from moving average technical rules

In this study we apply six moving average trading rules: SMA[5], SMA[10], SMA[15], MA[5,50], MA[5,150], and MA[5,200]. After observing buy and sell signals, we calculate returns from each signal. We classify the returns into returns generated from buy signals (RGBS), and return generated from sell signals (RGSS). The mean of RGBS for each technical rule for all stocks are presented in Table 3.

From the results we learn that all SMA rules generate positive RGBS for all stocks. Meanwhile, MA[5,50] only generates positive RGBS for two stocks, and MA[5,150] only generates positive RGBS for one stock. MA[5,200] performs better than the other two MAs since it generates positive RGBS for eight out of 15 stocks.

Next, we observe the sell signals after applying all six technical rules to all 15 stocks in the sample. The mean of RGSS for each moving average technical rule for all stocks are presented in Table 4. Similar to RGBS, all three SMA technical rules generate positive RGSS for all stocks. Worse than RGBS, both MA[5,50] and MA[5,150] produce negative RGSS for all stocks. Conversely, MA[5,200] seems to gener-

Table 4. Summary of returns generated from sell signals (RGSS)

This table presents the mean returns generated from sell signals (RGSS) after employing SMA[5], SMA[10], SMA[15], MA[5,50], MA[5,150], and MA[5,200] technical trading rules.

	SMA[5]	SMA[10]	SMA[15]	MA[5,50]	MA[5,150]	MA[5,200]
BUMI	0.002248	0.001766	0.001007	-0.000109	-0.000057	0.000023
TLKM	0.001167	0.000985	0.000603	-0.000052	-0.000031	0.000033
ADRO	0.001692	0.001304	0.000831	-0.000087	-0.000044	0.000034
ASII	0.001053	0.000777	0.000612	-0.000046	-0.000017	0.000020
BBRI	0.001472	0.001172	0.000748	-0.000056	-0.000028	0.000040
TRUB	0.001645	0.001247	0.000884	-0.000070	-0.000048	-0.000010
BDMN	0.001471	0.001144	0.000827	-0.000081	-0.000059	0.000048
ITMG	0.001109	0.000846	0.000695	-0.000049	-0.000043	0.000030
BBNI	0.001509	0.001220	0.000773	-0.000072	-0.000037	0.000028
MIRA	0.001917	0.001573	0.001043	-0.000102	-0.000068	-0.000049
SGRO	0.001492	0.001192	0.000850	-0.000067	-0.000056	0.000024
ELSA	0.002137	0.001811	0.001096	-0.000155	-0.000061	0.000032
INKP	0.001330	0.001032	0.000800	-0.000050	-0.000055	0.000063
CTRA	0.002046	0.001679	0.001256	-0.000105	-0.000056	-0.000049
CTRP	0.001959	0.001635	0.001186	-0.000093	-0.000048	-0.000044
Overall	0.001616	0.001310	0.000881	-0.000080	-0.000047	0.000015

Table 5. Summary of moving average technical rules applications

This table presents the result of employing SMA[5], SMA[10], SMA[15], MA[5,50], MA[5,150], and MA[5,200] technical trading rules. N(Buy) is the average number of buy signals. N(Sell) is the average number of sell signals. RGBS is the mean of returns generated from buy signals (RGBS). RGSS is the mean of returns generated from sell signals (RGSS). RGBS>0 is the proportion of RGBS greater than 0. RGSS>0 is the proportion of RGSS greater than 0. RGBS-RGSS shows the mean difference between RGBS and RGSS (RGBS less RGSS).

	N(Buy)	N(Sell)	RGBS	RGSS	RGBS>0	RGSS>0	RGBS-RGSS
SMA [5]	14,676.60	8,740.60	0.00173	0.00162	0.17378	0.18137	-0.00012
SMA [10]	13,269.40	10,355.80	0.00143	0.00131	0.16005	0.16227	-0.00012
SMA [15]	12,743.20	11,015.40	0.00100	0.00088	0.13743	0.13636	-0.00012
MA [5,50]	449.80	449.60	-0.00004	-0.00008	0.00260	0.00115	0.00004
MA [5,150]	258.80	259.00	-0.00003	-0.00005	0.00165	0.00072	0.00002
MA [5,200]	50.20	16.80	0.00003	0.00002	0.15248	0.05694	0.00002
Average	6,908.00	5,139.53	0.00069	0.00062	0.10466	0.08980	-0.00005

ate better RGSS than RGBS. It produces positive RGSS for 11 out of 15 stocks in the sample.

Looking at overall returns in Table 3 and Table 4,which are also summarized in Table 5, all three SMAs and MA[5,200] tend to generate positive RGBS and RGSS. Additionally, the overall RGBS are higher than RGSS. SMA[5] on average generates around 0.173% RGBS and 0.162% RGSS. SMA[10] on average creates 0.143% RGBS and 0.131% RGSS. SMA[15] on average produces 0.1% RGBS and 0.088% RGSS. In the mean time, MA[50,200] on average generates 0.003% RGBS and 0.002% RGSS.

In contrast, MA[5,50] and MA[5,150] seem to generate negative overall RGBS and RGSS, although RGBS is less negative than RGSS. MA[5,50] on average generates -0.004% RGBS and -0.00% RGSS. MA[5,150] on average generates -0.003% RGBS and -0.005% RGSS. From the descriptions of RGBS and RGBS, SMA technical trading rules seem to perform better than MA trading rules for intraday stock trading.

Table 5 presents the summary of each moving average technical trading rule. All three SMAs tend to generate more buy signals than sell signals. SMA[5] on average generates 14,676 buy signals and 8,740 sell signals. SMA[10] on average produces 13,269 buy signals and only 10,355 sell signals. MA[5,50] and MA[5,150] seem to generate relatively equal numbers of buy and sell signals, which are around 450 and 259 signals respectively. Meanwhile, MA[5,200] correspondingly generates around 50 buy and 17 sell signals.

Table 6. Paired *t*-test summary

We perform two-tail *t*-tests of mean return differences for all six technical trading rules applied on all stocks in the sample. The *p*-value is presented in parentheses. RGB-UBS is the mean difference betweenreturn generated from buy signal (RGBS) and unconditional basic return (UBR). RGSS-UBR is the mean difference between return generated from sell signal (RGSS) and UBR. RGBS-RGSS is the mean difference between RGBS and RGSS.

	RGBS-UBR (*p*-value)	RGSS-UBR (*p*-value)	RGBS-RGSS (*p*-value)
SMA[5]	0.00173414 (0.0000)	0.00161632 (0.0000)	0.00011782 (0.0000)
SMA[10]	0.00142797 (0.0000)	0.00130971 (0.0000)	0.00011826 (0.0000)
SMA[15]	0.00099621 (0.0000)	0.00088075 (0.0000)	0.00011583 (0.0000)
MA[5,50]	-0.00004390 (0.0000)	-0.00007963 (0.0000)	0.00003574 (0.0000)
MA[5,150]	-0.00002877 (0.0000)	-0.00004715 (0.0000)	0.00001838 (0.0000)
MA[5,200]	0.00003022 (0.0009)	0.00001490 (0.0000)	0.00001529 (0.0026)

Table 5 also presents the proportions of positive RGBS and RGSS generated from applying each technical trading rule. SMA[5] generates the highest positive returns proportion of 17.38% RGBS and 18.14% RGSS. Meanwhile, MA[5,50] generates the lowest positive returns proportion of only 0.26% RGBS and around 0.12% RGSS. All three SMAs tend to generate higher RGBS than RGSS, with differences of around 0.012%. On the contrary, all three MAs tend to produce lower RGBS than RGSS.

From Table 6 we learn that all *t*-tests exhibit significant mean return differences. The test shows that SMA[5] respectively produces the highest excess RGBS and RGSS of around 0.17% and 0.16% more than UBR. In contrast, MA[5,50] performs the worst with RGBS and RGSS of around 0.0044% and 0.0080% below UBR.

For all six technical rules, the tests show that the mean of RGBS are steadily higher than the mean of RGSS. This finding is consistent with Brock et al. (1992), who also find returns generated from buy signals are higher than returns generated from sell signals. Moreover, all three SMAs consistently produce better RGBS and RGSS compared to all three MAs, confirming the superiority of SMAs over MAs.

Conclusion

We find that all three SMA technical trading rules: SMA[5], SMA[10], and SMA[15] applied to 15 stocks in the sample, produce consistent positive returns in both return generated from buy signal (RGBS) and return generated from sell signal (RGSS). In contrast, all three MA technical trading rules: MA[5,50], MA[5,150], MA[5,200] do not deliver consistent positive returns. MA[5,200] performs slightly better than the other two MAs.

Based on the *t*-tests of mean differences, we find SMA[5], SMA[10], SMA[15], and MA[5,200] significantly produce positive excess RGSS and RGBS above unconditional basic return (UBR). In contrast, MA[5,50] and MA[5,150]significantly produce RGSS and RBSS less than UBR. Consequently, we can conclude that all three SMAs consistently perform better than their MAs counterparts.

We realize the sample size of this research is relatively small, thus our results may not be applicable for the general population. Therefore, we suggest further research using more stocks as the sample, or apply bootstrap methodology as suggested by Brock et al. (1992).

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