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EFFICIENCY OF THE STOCK MARKETS AFTER THE 2008 FINANCIAL CRISIS: EVIDENCE FROM THE FOUR ASIAN DRAGONS

Ka Po Kung
National University of Singapore, Singapore
E-mail: kckung@u.nus.edu

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Abstract

The efficient market hypothesis (EMH) claims that in an efficient market where prices of securities fully reflect their intrinsic values, it is not possible to make excess returns with any investment tools or strategies. A natural question then to ask is: has the EMH claim become obsolete or irrelevant after the 2008 financial crisis? To address this issue, this study employs three popular technical trading rules to investigate, using the 10-year daily price data after the crisis, the efficiency of the stock markets of Hong Kong, Korea, Singapore, and Taiwan — jointly known as the four Asian dragons. Our rationale for using these rules is that if they are effective in exploiting profit opportunities, then these markets are not efficient. Our results show that, with a few minor exceptions in Hong Kong and Singapore, none of the three rules performs better than a buy-and-hold strategy. Given these results, we conclude that the EMH claim is still alive and well in these four stock markets. In practice, many corporations operating in the four Asian Dragons typically turn to banks for financing. Hence, an important implication of this study is that, given the efficiency of the four markets, these corporations should instead step up the use of the stock markets to raise the needed funds, which is more likely to lower their cost of financing.

Keywords: Efficient Market Hypothesis, Technical Rules, Efficiency, Four Asian Dragons, Buy-and-Hold Strategy

1. Introduction

The efficient market hypothesis (EMH), first formulated by Fama (1965, 1970), claims that security prices in an efficient market fully reflect all available information. In an efficient market, competition among numerous rational, profit-seeking investors leads to a situation where security prices, at any point in time, reflect all relevant information based both on events, which have happened and on events which the market as a whole expects to happen in the future. In other words, market prices of securities at any time are good estimates of their fundamental or intrinsic values.

The EMH enjoyed a glorious heyday in the 1970s when its claim caught on in the academic and investment worlds. In the former, numerous empirical studies based on extensive security price data were conducted and almost universally supported the validity of the EMH claim. Jensen (1978, p. 95) claimed that “there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Markets Hypothesis.” In the latter,

investment attitudes among investors, especially large institutional investors, changed from active management (involving ongoing buying and selling actions to exploit profit opportunities) to passive management (involving a long-term, buy-and-hold approach to investing) with the popularization of the EMH.

However, the EMH has been subjected to serious challenges since the early 1980s from many economists. Two major empirical challenges were made. The first is that many studies have indicated that stock prices are predictable. For example, Fama and French (1988) showed that there is notable predictability of stock returns over long horizons, Poterba and Summers (1988) found significant mean reversion in stock returns for long periods, and Lo and MacKinlay (1990) discovered that short-term serial correlations of stock returns are statistically significant. The second is that many studies have revealed a number of so-called anomalies in the stock market, which are not consistent with the EMH. These anomalies (Banz, 1981; Akbas *et al.* 2015; Barberis *et al*. 2021) include the small-firm effect (i.e., smaller-firm stocks appear to outperform larger-firm stocks on a risk-adjusted basis), the January effect (i.e., stock returns tend to be higher in January than in other months of the year), and the day-of-the-week effect (i.e., stock returns appear to be lower on Mondays than on other days of the week).

In particular, the 2008 financial crisis led to harsh criticism of the EMH from both academics and investment professionals alike. Posner (2009, p. 127) argued that "U.S. lax monetary policy and deregulation helped lead to the crisis because policy makers had too much faith in the efficient market claim." Jeremy Grantham, a noted market analyst, laid the blame squarely on the EMH for the crisis (Nocera, 2009), pointing out that the inaccurate efficient market theory caused a lethally dangerous combination of asset bubbles, lax controls, pernicious incentives, and complicated instruments that led to the stock market meltdown.

Has the EMH claim become obsolete or irrelevant after the 2008 financial crisis? To address this issue, this study makes use of three technical trading rules to investigate, over the ten years after the crisis, the efficiency of the stock markets of Hong Kong, Korea, Singapore, and Taiwan, which are collectively known as the four Asian dragons. Our rationale for using these technical rules is that if they are effective in exploiting profit opportunities, then we can conclude that these markets are not efficient. By most classification criteria, Hong Kong and Singapore are classified as developed markets, and Korea and Taiwan as emerging markets. We choose these four markets as the testing grounds for this study because they played an important role in the economic recovery of Asia after the crisis. That said, employing a buy-and-hold strategy as the benchmark for comparison, this research uses the following three simple but popular technical trading rules – single moving average, double moving average, and trading range break – to investigate the efficiency of the four Asian stock markets over the ten years after the 2008 financial crisis.

To achieve an accurate as well as thorough investigation of their effectiveness, our implementation of the technical rules sets this research apart from most of the previous related studies in three ways. First, most studies (e.g., Brock *et al.* 1992; Bessembinder and Chan, 1995; Fernandez-Rodriguez *et al.* 2000; Siegel, 2002) ignore two things when they compute returns for the rules. One is that they do not consider trading costs associated with buying or selling stocks. For the four stock markets, trading costs consist of a brokerage fee and a trading tax. The other is that they ignore interest incomes that can be earned when investors are out of the market. In this study, we take trading costs and interest incomes into account. Second, unlike many studies, which examine only a few technical rules, we investigate a range of different versions (20-day, 50-day, 100-day, 150-day, 200-day, and 250-day) of each of the three technical rules. Such a range is wide enough to encompass most of the three rules used in practice. Third, in addition to the entire 2009-2018 period, we also investigate their effectiveness over the 2009-2013 and 2014-2018 subperiods, where the former spans the five years when the effect of the 2008 crisis was still in full force, and the latter spans the five years when its effect was basically unnoticeable.

The rest of this paper is organized as follows: Section 2 reviews the related literature on stock market efficiency and technical analysis. Section 3 presents the data and reports the trading costs for trading stocks in the four markets. Section 4 describes the three technical rules in detail. Section 5 presents and discusses the empirical results for the four markets. Section 6 concludes this study and suggests some possible future related research.

2. Literature review

There is a huge amount of literature related to stock market efficiency and technical analysis. In this literature review, we address first the former and then the latter based on some relevant studies.

2.1. Stock market efficiency

The history of the notion of efficient markets dates back Bachelier (1900, p. 32) who claimed that "the market does not believe, at any given instant, in a rise nor a fall in the true price." That said, Bachelier (1900) developed a set of mathematical expressions to depict the random nature of stock prices. Samuelson (1965) and Fama (1965) theorized his random characterization of stock prices with the random walk theory – and the efficient market hypothesis (EMH) was born.

Empirical studies in the 1960s and 1970s (e.g., Alexander, 1964; Fama and Blume, 1966; Van Horne and Parker, 1967, 1968; James, 1968; Jensen and Benington, 1970; Jensen, 1978) lend strong support to the EMH. However, empirical studies in the 1980s and 1990s (e.g., Keim and Stambaugh, 1986; Poterba and Summers, 1988; Lo and MacKinlay, 1988; Jegadeesh and Titman, 1993) found evidence against the EMH. In particular, the following two main issues since the 1980s are clearly at odds with the implication of the EMH: one is predictability in stock returns and the other is market anomalies.

There is abundant evidence that stock returns are predictable in both developed and emerging stock markets. Keim and Stambaugh (1986) showed that bond market data, such as the spread between yields on high-grade and low-grade corporate bonds, provide information to predict stock market returns. Jegadeesh and Titman (1993), investigating intermediate-horizon (3-month to 12-month holding periods) stock price behavior, found that portfolios of the best-performing stocks outperform other stocks and lead to substantial profit opportunities. Serletis and Rosenberg (2009) used daily data on four U.S. stock market indices and found that the indices exhibit pronounced negative long-term serial correlation. Kang *et al*. (2010) investigated the daily prices of the Korean stock market and found long-term mean-reversion property in the KOSPI 50 index and its 50 constituent stock prices. Rege and Martin (2011) examined the Portuguese stock market index and concluded that it exhibits both long and short memories. Mishra *et al.* (2011), using a long series of daily price data for the Indian stock market, found strong evidence of persistence and temporal dependencies in stock returns. Boubaker and Makram (2012) found strong evidence of long-term memory in North African stock market returns.

Many empirical studies have shown a number of market anomalies, which are inconsistent with the EMH. Banz (1981), using New York Stock Exchange (NYSE) stock data, found that average annual returns are consistently higher for small-firm portfolios than for large-firm portfolios. Ritter (1988) showed that on a yearly basis, the ratio of stock purchases to stock sales of individual investors reaches an annual low at the end of December and an annual high at the beginning of January. Chopra *et al.* (1992) found strong tendencies for stocks performing poorly in one period to experience sizable reversals over the subsequent period, while the best-performing stocks in a given period tend to follow with poor performance in the next period. In recent research, Narayan and Zheng (2010), using daily data for all the stocks traded on the Shanghai Stock Exchange from 1993 to 2003, applied the cross-sectional stock return model with the market liquidity risk factor on the Chinese stock market and found that their model can capture significant stock market anomalies, which include size, book-to-market ratio, and turnover rate. Bauer *et al.* (2010), using monthly stock returns and market values for a wide range of stocks from 16 European countries from February 1985 to June 2002, found that small-growth portfolios exhibit substantial positive pricing errors and a set of macroeconomic and portfolio-specific variables have obvious predictive power for these small-growth portfolios. Akbas *et al.* (2015), using mutual funds as proxy for dumb money and hedge funds as proxy for smart money, found that returns from hedge funds are consistently higher than those from mutual funds. Barberis *et al.* (2021), using data of all stocks listed on the NYSE, NASDAQ, and Amex from July 1963 to December 2014, developed an asset price model, based on prospect theory, to examine 23 stock market anomalies and found that their model can capture a majority of the 23 anomalies.

2.2. Technical analysis

The oldest technical rule is considered to have been developed by a Japanese rice merchant named Munehisa Homma (1724-1803), who traded in the Dojima Rice Exchange in Osaka during the 18th century. Homma made use of Yin and Yang from the I Ching (or the Book of Changes) to depict the alternation between a bear rice market (Yin) and a bull rice market (Yang). He developed the candlestick chart for timing his trading and, as a result, accumulated a huge fortune. He is often regarded to be the father of the candlestick chart. However, most market technicians nowadays attribute technical analysis to Charles Dow (1851-1902), who co-founded the Wall Street Journal in 1889. In the journal, Dow published regularly his ideas of technical analysis in a series of editorials. In 1932, Robert Rhea, an exponent of Dow's ideas of technical analysis, integrated his scattered ideas into a set of rules and published them in a book entitled *Dow Theory*.

Early studies do not lend support to technical analysis. Using 30-plus years of data on the Dow Jones Industrial Average (DJIA) and the Standard and Poor's 500, Alexander (1964) conducted extensive tests of technical rules and concluded that their performance is no better than a buy-and-hold (BH) strategy when transaction costs are taken into account. Fama and Blume (1966) examined the profitability of technical rules using daily data from 1956 to 1962 of 30 individual DJIA stocks and concluded that they do not generate profits higher than those of a BH strategy. Other empirical studies (e.g., Van Horne and Parker, 1967; James, 1968; Jensen and Benington, 1970), using U.S. stock data, also found evidence that returns from technical rules are no higher than those from a BH strategy.

However, recent empirical studies have produced mixed findings. Some studies (e.g., Zhu and Zhou, 2009; Lin *et al.* 2011; Han *et al.* 2013; Manahov *et al.* 2014) tend to support the effectiveness of technical rules. Zhu and Zhou (2009), using monthly returns from December 1926 to December 2004 on the S&P 500, found that many moving average rules outperform the optimal dynamic strategies considerably. Han *et al.* (2013), grouping moving average portfolios based on their levels of volatility, found that such portfolios generate abnormal returns higher than those from the well-known momentum strategy and outperform the buy-and-hold strategy. Manahov *et al.* (2014), applying an adaptive form of the Strongly Typed Genetic Programming (STGP)-based learning algorithm to the foreign exchange market, found that the excess returns are both statistically and economically significant for such foreign currencies as Euro, Australian dollar, British pound, Canadian dollar, Japanese Yen, and Swiss franc.

On the other hand, some other studies (e.g., Marshall *et al.* 2008a and 2008b; Shynkevich, 2012; Zhu *et al.* 2015) do not lend support to the usefulness of technical rules. Marshall *et al.* (2008a), examining 7,846 technical rules from five major categories (i.e., channel breakout, filter, moving average, on-balance volume, support and resistance rules), concluded that most of the rules are not profitable in the U.S. equity market. Shynkevich (2012) examined a set of almost 13,000 technical rules and concluded that they are basically useless, in terms of profitability, with respect to six U.S. technology industry indices and nine small cap sector indices over the period from 1995 to 2010. Zhu *et al.* (2015), using daily price data from the Shanghai Stock Exchange Composite Index and the Shenzhen Stock Exchange Composite Index from 1991 to 2013, investigated the profitability of some popular technical rules (e.g., moving average and trading range breakout) and concluded that these rules perform no better than a simple buy-and-hold strategy, especially when transaction costs are taken into account.

3. Time series data and trading costs

We retrieved two sets of daily time series data, each of which contains 2,608 observations, from 2009 to 2018 from the DataStream database for use in this study. One set of data is the daily prices of the stock indices of the four stock markets. They are the Hang Seng Index of Hong Kong, the Korea Composite Stock Price Index of Korea, the Straits Times Index of Singapore, and the Taiwan Stock Exchange Weighted Index of Taiwan. See Figures 1 and 2 for the evolutions of the four market indices from 2009 to 2018. The other set of data is the daily interest rates of the four

markets. They are the Hong Kong dollar one-month rate, the Bank of Korea base rate, the Singapore dollar one-month rate, and the Taiwan dollar one-month rate.

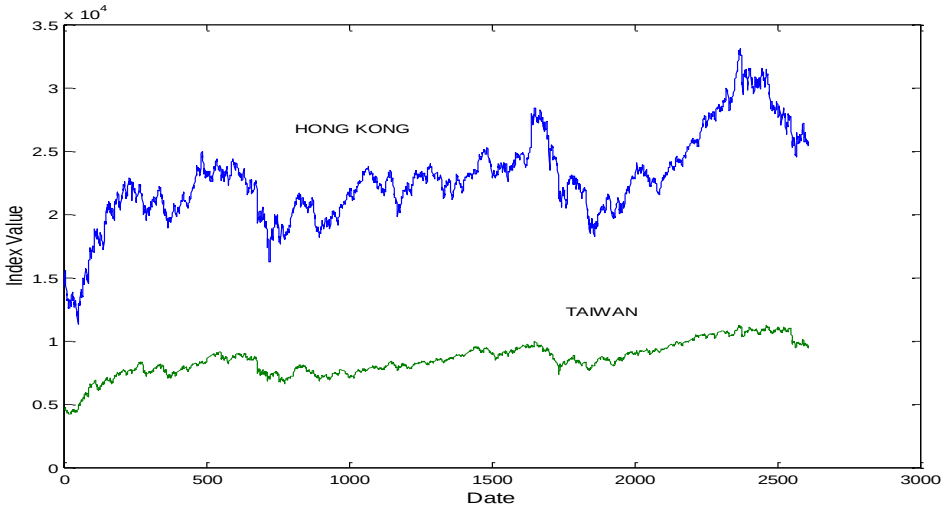

Figure 1. Market indices from 2009 to 2018 for Hong Kong and Taiwan

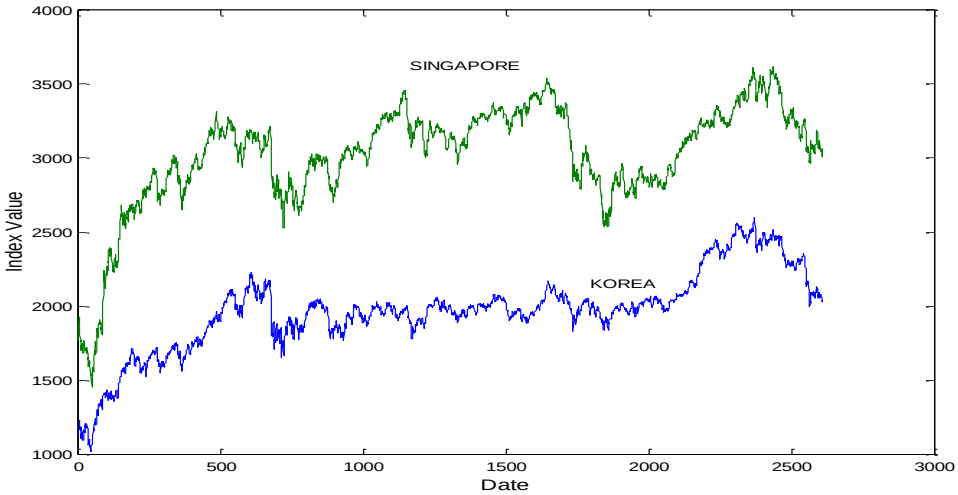

Figure 2. Market indices from 2009 to 2018 for Korea and Singapore

Table 1 shows the autocorrelations of one-day returns at lag *i* for each time series of the four market indices, where *i* = 1, 2, 3, 4, 5. If a stock market is efficient, then autocorrelations should be statistically insignificant. In other words, the change in stock return today should be unrelated to the change that occurred yesterday, the day before, or any other day in the past. However, two phenomena are evident from Table 1. First, for each market index, large autocorrelation occurs at fixed time lag. For example, autocorrelation with 1% level of significance occurs at lag 4 for Hong Kong, at lag 5 for Korea, at lag 1 for Singapore, and at lag 1 for Taiwan. Second, there are large autocorrelations occurring more often in the 2014-2018 subperiod than in either the 2009-2018 period or the 2009-2013 subperiod. Specifically, in the 2014-2018 subperiod, autocorrelation with 1% level of significance occurs two times for Hong Kong, three times for Korea, two times for Singapore, and two times for Taiwan. Given these two phenomena, this study is intended to investigate whether the technical rules are capable of detecting and translating them into excess returns.

Table 1. **Autocorrelations of 1-day returns for the four stock markets**

	Hong Kong	Korea	Singapore	Taiwan
2009-2018				
Mean	0.0002	0.0002	0.0002	0.0003
Standard Deviation	0.0124	0.0100	0.0090	0.0099
C(1)	0.0173	0.0024	0.0456**	0.0406**
C(2)	0.0023	-0.0143	0.0156	-0.0164
C(3)	0.0236	0.0029	0.0284*	0.0028
C(4)	-0.0513**	-0.0229*	-0.0268*	-0.0189
C(5)	-0.0169	-0.0518**	0.0083	-0.0068
2009-2013				
Mean	0.0004	0.0004	0.0005	0.0005
Standard Deviation	0.0139	0.0121	0.0105	0.0114
C(1)	0.0186	0.0042	0.0513**	0.0586**
C(2)	-0.0036	-0.0364**	0.0299*	-0.0276*
C(3)	0.0263	0.0081	0.0279*	-0.0164
C(4)	-0.0629**	-0.0168	-0.0334**	-0.0192
C(5)	-0.0009	-0.0552**	0.0020	0.0224
2014-2018				
Mean	0.0001	0.0000	0.0000	0.0001
Standard Deviation	0.0106	0.0073	0.0073	0.0081
C(1)	0.0147	-0.0043	0.0320**	0.0033
C(2)	0.0119	0.0447**	-0.0155*	0.0052
C(3)	0.0190	-0.0115	0.0289**	0.0402**
C(4)	-0.0319**	-0.0407**	-0.0153*	-0.0186*
C(5)	0.0147	-0.0448**	0.0195*	-0.0651**

Note: C(i) is the autocorrelation estimated at lag i for each series, where i = 1, 2, 3, 4, 5. Autocorrelations with * (**) are significant at the 5% (1%) level.

The trading costs[1] for trading stocks in the four markets are as follows. In Hong Kong, the cost consists of a stamp duty of 0.1125% of the trading amount for buy/sell trades and a brokerage fee ranging from 0.25% to 0.5% of the trading amount. We use 0.3% for the brokerage fee. In Korea, the cost consists of a trade tax of 0.15% of the trading amount for sell trades and a brokerage fee ranging from 0.3% to 0.5% of the trading amount. We use 0.4% for the brokerage fee. In Singapore, the cost consists of a clearing fee of 0.05% and a brokerage fee of 0.2% of the trading amount. In Taiwan, the cost consists of a trade tax of 0.1425% of the trading amount for sell trades and a brokerage fee of 0.3% of the trading amount.

4. The three technical rules investigated

The three technical trading rules used in this study are single moving average, double moving average, and trading range break (see Brock *et al.* 1992; Murphy, 1999; Edwards *et al.* 2018). A moving average of a stock index is simply the average of a given number of past closing prices of the index. Letting P_i be the closing price of the index on day *i*, we have that the *n*-day moving average (M-A) on day *t* is given by

$$MA_{t,n} = \frac{1}{n}\sum_{i=t-n+1}^{t} P_i = \frac{1}{n}[P_{t-n+1} + P_{t-n+2} + \ldots + P_t] \quad (1)$$

A moving average of an index is far less volatile than the index itself. When index price is rising, the moving average trails the index and forms a support level for index price. When index price is falling, the moving average is above the index and forms a resistance level. As technical

[1] Information for the trading costs was obtained from the websites of the four stock market exchanges.

analysts often put it, a moving average allows investors to identify the basic market trend without being affected by the daily volatility of the market.

According to single moving average (S-M-A), a buy signal is generated when the closing price of the index rises above the *n*-day M-A and a sell signal is generated when the closing price falls below the *n*-day M-A. When a buy/sell signal is generated and implemented, S-M-A rules require that the position be maintained until the closing price penetrates through the *n*-day M-A again. A popular S-M-A rule is 200-day M-A, where 200 stands for the past 200 days' closing prices. In this study, we examine the following six versions of the S-M-A rules: 20-day, 50-day, 100-day, 150-day, 200-day, and 250-day. A one-percent band is used to reduce the number of times an investor will have to move into and out of the market. That is, whenever the index closes at least one percent above the n-day M-A, the index is purchased at its closing price. On the other hand, whenever the index closes at least one percent below the n-day M-A, the index is sold.

According to double moving average (D-M-A), buy and sell signals are generated by a long M-A and a short M-A. Buy (sell) signals are generated when the short M-A rises above (falls below) the long MA by a prespecified percentage band. In this study, we investigate the following six versions of the D-M-A rules: 20-2, 50-2, 100-10, 150-10, 200-10, and 250-10, where the first number is the number of days of a long M-A and the second number is the number of days of a short M-A. Again, a one-percent band is used to reduce the number of times an investor will have to move into and out of the market.

According to trading range break (T-R-B), a buy signal is generated when the closing price of the index rises above a local maximum (i.e., the maximum price over the past certain number of days) and a sell signal is generated when the closing price falls below a local minimum (i.e., the minimum price over the past certain number of days). In this study, we use *Max*(*m,t*) for an *m*-day local maximum on day *t* and *Min*(*m,t*) for an *m*-day local minimum on day *t*. That is,

$$Max(m,t) = max[P_{t-m}, P_{t-m+1}, \ldots, P_{t-1}] \quad (2)$$

$$Min(m,t) = min[P_{t-m}, P_{t-m+1}, \ldots, P_{t-1}] \quad (3)$$

where *Max*(*m,t*) is the maximum value of the index over the past m days and *Min*(*m,t*) is the minimum value of the index over the past m days. Accordingly, a buy signal is generated if $P_t >$ *Max*(*m,t*) and a sell signal is generated if $P_t <$ *Min*(*m,t*). In this study, we investigate the following six versions of the T-R-B rules: 20-day, 50-day, 100-day, 150-day, 200-day, and 250-day. Again, we use a one-percent band where the index level must rise above the local maximum for a buy signal and fall below the local minimum for a sell signal.

5. Results and discussions

If the four stock markets are efficient, then the three technical rules should not be able to generate excess returns. In this regard, we use a buy-and-hold (B-H) strategy as a benchmark against which the annualized returns from the three technical rules are compared. A buy-and-hold strategy is an investment technique whereby an investor buys stocks and holds them for a long time, regardless of market conditions. Table 2 shows the starting values and ending values of the four market indices for the entire period and the two subperiods. Tables 3 to 6 present the annualized returns, abbreviated as returns, from the three technical rules for Hong Kong, Korea, Singapore, and Taiwan, respectively. "Buy-Hold" represents the corresponding buy-and-hold strategy. "No Cost" and "Cost" indicate whether trading costs are not included or included in the computations. Annualized return $R_T(i,j)$ from rule *i* for the period *j* of *T* years (where *j* = 2009-2018, 2009-2013, 2014-2018) is given by

$$R_T(i,j) = exp\left[\frac{log(P_T) - log(P_0)}{T}\right] - 1 \quad (4)$$

where P_0 and P_T are the closing prices of the index on the first day and the last day of the period, *T* is the number of years of the period, and "*log*" stands for natural logarithm.

Table 2. **Starting values and ending values of the four indices for the three periods**

Period	Hong Kong	Korea	Singapore	Taiwan
2009 – 2018				
02-01-2009	15042.81	1157.40	1829.71	4591.22
31-12-2018	25845.70	2041.04	3068.76	9727.41
2009 – 2013				
02-01-2009	15042.81	1157.40	1829.71	4591.22
31-12-2013	23306.39	2011.34	3167.43	8611.51
2014 – 2018				
02-01-2014	23340.05	1967.19	3174.65	8612.54
31-12-2018	25845.70	2041.04	3068.76	9727.41

5.1. Annualized returns for the four markets

Table 3 shows the returns for the Hong Kong market. On average, all the three rules perform no better than the corresponding B-H strategies for the 2009-2018 entire period and the 2009-2013 subperiod with or without trading costs. For example, for the 2009-2013 subperiod, the average return is -0.0152 for the S-M-A rules, -0.0201 for the D-M-A rules, and 0.0487 for the T-R-B rules with trading costs, compared to 0.0897 under the corresponding B-H strategy. For the 2014-2018 subperiod, some versions of the three rules perform better than their corresponding B-H strategies. For example, without trading costs, the return is 0.0539 for the 100-day S-M-A rule, 0.0771 for the 250-10 D-M-A rule, and 0.0251 for the 20-day T-R-B rule, compared to a return of 0.0206 under the corresponding B-H strategy.

Table 3. **Annualized returns of the three rules for Hong Kong stock market**

Rules	2009-2018		2009-2013		2014-2018	
	No Cost	Cost	No Cost	Cost	No Cost	Cost
Buy-Hold	0.0556	0.0548	0.0915	0.0897	0.0206	0.0189
S-M-A						
20-day	0.0304	-0.0431	0.0808	0.0058	-0.0177	-0.0896
50-day	0.0497	0.0064	0.0516	0.0010	0.0530	0.0190
100-day	0.0382	0.0129	0.0352	0.0069	0.0539	0.0345
150-day	0.0086	-0.0150	0.0009	-0.0185	0.0172	-0.0076
200-day	-0.0064	-0.0256	-0.0283	-0.0471	0.0452	0.0303
250-day	0.0037	-0.0137	-0.0204	-0.0393	0.0647	0.0581
Average	0.0207	0.0130	0.0200	-0.0152	0.0360	0.0075
D-M-A						
20-2	0.0220	-0.0421	0.0389	-0.0292	0.0054	-0.0547
50-2	0.0685	0.0329	0.0862	0.0446	0.0582	0.0303
100-10	0.0428	0.0289	0.0270	0.0113	0.0703	0.0615
150-10	-0.0041	-0.0183	-0.0251	-0.0400	0.0148	0.0023
200-10	-0.0046	-0.0148	-0.0489	-0.0615	0.0554	0.0489
250-10	0.0050	-0.0043	-0.0346	-0.0455	0.0771	0.0727
Average	0.0216	-0.0029	0.0073	-0.0201	0.0469	0.0268
T-R-B						
20-day	0.0676	0.0670	0.1164	0.1152	0.0250	0.0240
50-day	0.0625	0.0619	0.1057	0.1046	0.0220	0.0209
100-day	0.0379	0.0371	0.0545	0.0535	0.0083	0.0037
150-day	0.0192	0.0187	0.0175	0.0164	0.0031	0.0019
200-day	0.0121	0.0116	0.0034	0.0024	-0.0029	-0.0053
250-day	0.0111	0.0106	0.0014	0.0003	-0.0029	-0.0053
Average	0.0350	0.0345	0.0498	0.0487	0.0088	0.0067

Note: Buy-Hold is the buy-and-hold strategy. “No Cost” and “Cost” indicate that the trading costs are not included and included, respectively.

Table 4 shows the returns for the Korea market. The three technical rules are basically useless in this market. Take the average returns with trading costs for illustration. For the 2009-

2018 period, the average return is -0.0230 for the S-M-A rules, -0.0206 for the D-M-A rules, and -0.0059 for the T-R-B rules, compared to 0.0574 under the corresponding B-H strategy; for the 2009-2013 subperiod, the average return is -0.0101 for the S-M-A rules, -0.0245 for the D-M-A rules, and 0.0082 for the T-R-B rules, compared to 0.1147 under the corresponding B-H strategy; for the 2014-2018 subperiod, the average return is -0.0220 for the S-M-A rules, -0.0056 for the D-M-A rules, and -0.0224 for the T-R-B rules, compared to 0.0055 under the corresponding B-H strategy.

Table 4. **Annualized returns of the three rules for Korea stock market**

Rules	2009-2018		2009-2013		2014-2018	
	No Cost	Cost	No Cost	Cost	No Cost	Cost
Buy-Hold	0.0584	0.0574	0.1169	0.1147	0.0074	0.0055
S-M-A						
20-day	0.0135	-0.0428	0.0427	-0.0235	-0.0085	-0.0546
50-day	0.0213	-0.0141	0.0506	0.0113	-0.0019	-0.0318
100-day	0.0020	-0.0244	0.0260	-0.0018	-0.0106	-0.0330
150-day	0.0013	-0.0185	-0.0007	-0.0222	0.0105	-0.0048
200-day	-0.0008	-0.0187	0.0043	-0.0098	0.0161	0.0007
250-day	-0.0028	-0.0197	-0.0006	-0.0147	0.0066	-0.0086
Average	0.0057	-0.0230	0.0204	-0.0101	0.0020	-0.0220
D-M-A						
20-2	0.0097	-0.0419	0.0382	-0.0222	-0.0123	-0.0546
50-2	0.0271	-0.0056	0.0573	0.0216	0.0020	-0.0263
100-10	0.0024	-0.0100	-0.0186	-0.0324	0.0293	0.0195
150-10	-0.0073	-0.0177	-0.0328	-0.0445	0.0195	0.0118
200-10	-0.0147	-0.0259	-0.0265	-0.0383	0.0162	0.0085
250-10	-0.0132	-0.0225	-0.0229	-0.0310	0.0152	0.0075
Average	0.0007	-0.0206	-0.0009	-0.0245	0.0117	-0.0056
T-R-B						
20-day	0.0095	-0.0077	0.0184	-0.0046	0.0007	-0.0107
50-day	0.0276	0.0198	0.0572	0.0492	-0.0013	-0.0088
100-day	-0.0026	-0.0083	0.0187	0.0129	-0.0235	-0.0291
150-day	0.0025	-0.0013	0.0185	0.0147	-0.0132	-0.0170
200-day	-0.0117	-0.0145	-0.0028	-0.0047	-0.0287	-0.0324
250-day	-0.0203	-0.0231	-0.0165	-0.0184	-0.0324	-0.0360
Average	0.0008	-0.0059	0.0156	0.0082	-0.0164	-0.0224

Note: Buy-Hold is the buy-and-hold strategy. “No Cost” and “Cost” indicate that the trading costs are not included and included, respectively.

Table 5 shows the returns for the Singapore market. The three technical rules are not effective for the 2009-2013 subperiod, during which the market index rises from 1829.71 on 2 January 2009 to 3167.43 on 31 December 2013. Over the subperiod, the average return with trading costs is 0.0227 for the S-M-A rules, 0.0046 for the D-M-A rules, and 0.0199 for the T-R-B rules, compared to 0.1149 under the corresponding B-H strategy. However, some versions of the three rules perform slightly better than the corresponding B-H strategies for the 2014-2018 subperiod, during which the market index falls from 3174.65 on 2 January 2014 to 3068.76 on 31 December 2018. Over the subperiod, the average return with trading costs is -0.0056 for the S-M-A rules, 0.0034 for the D-M-A rules, and -0.0083 for the T-R-B rules, compared to -0.0078 under the corresponding B-H strategy.

Table 5. **Annualized returns of the three rules for Singapore stock market**

Rules	2009-2018		2009-2013		2014-2018	
	No Cost	Cost	No Cost	Cost	No Cost	Cost
Buy-Hold	0.0531	0.0526	0.1160	0.1149	-0.0068	-0.0078
S-M-A						
20-day	0.0444	0.0150	0.1014	0.0694	-0.0038	-0.0304
50-day	0.0390	0.0230	0.0832	0.0660	-0.0010	-0.0159
100-day	0.0276	0.0168	0.0476	0.0361	0.0018	-0.0082
150-day	0.0172	0.0101	0.0163	0.0102	0.0068	-0.0012
200-day	-0.0006	-0.0086	-0.0035	-0.0115	0.0008	-0.0072
250-day	0.0035	-0.0035	-0.0233	-0.0340	0.0314	0.0294
Average	0.0218	0.0088	0.0370	0.0227	0.0060	-0.0056
D-M-A						
20-2	0.0325	0.0070	0.0917	0.0641	-0.0155	-0.0389
50-2	0.0407	0.0273	0.0741	0.0591	0.0110	-0.0011
100-10	0.0002	-0.0073	-0.0115	-0.0204	0.0090	0.0030
150-10	0.0035	-0.0016	-0.0144	-0.0193	0.0117	0.0066
200-10	0.0070	0.0025	-0.0108	-0.0167	0.0238	0.0207
250-10	-0.0020	-0.0060	-0.0336	-0.0394	0.0319	0.0298
Average	0.0137	0.0037	0.0159	0.0046	0.0120	0.0034
T-R-B						
20-day	0.0441	0.0374	0.1075	0.0987	-0.0156	-0.0205
50-day	0.0429	0.0392	0.0722	0.0679	0.0143	0.0113
100-day	-0.0006	-0.0026	0.0050	0.0020	-0.0062	-0.0071
150-day	-0.0107	-0.0122	-0.0152	-0.0171	-0.0062	-0.0071
200-day	-0.0006	-0.0016	-0.0067	-0.0082	-0.0092	-0.0102
250-day	-0.0116	-0.0126	-0.0226	-0.0241	-0.0151	-0.0161
Average	0.0106	0.0080	0.0234	0.0199	-0.0063	-0.0083

Note: Buy-Hold is the buy-and-hold strategy. “No Cost” and “Cost” indicate that the trading costs are not included and included, respectively

Table 6 shows the returns for the Taiwan market. The three technical rules are not effective at all in this market. Many of these rules result in negative returns. Specifically, when the trading costs are taken into consideration, more than half of them, be they of S-M-A rules, D-M-A rules, or T-R-B rules, are in the negative territory in terms of returns. For example, for the 2014-2018 subperiod, there are five negative returns out of the six S-M-A rules, four negative returns out of the six D-M-A rules, and six negative returns out of the six T-R-B rules.

Let’s look at their returns on an average basis. For the 2009-2018 entire period, the average return with trading costs is -0.0007 for the S-M-A rules, -0.0012 for the D-M-A rules, and 0.0004 for the T-R-B rules, compared to 0.0773 under the corresponding B-H strategy. For the 2009-2013 subperiod, the average return with trading costs is 0.0191 for the S-M-A rules, 0.0185 for the D-M-A rules, and 0.0226 for the T-R-B rules, compared to 0.1327 under the corresponding B-H strategy. For the 2014-2018 subperiod, the average return with trading costs is -0.0214 for the S-M-A rules, -0.0206 for the D-M-A rules, and -0.0328 for the T-R-B rules, compared to 0.0234 under the corresponding B-H strategy. In particular for the 2014-2018 subperiod, even when the trading costs are not taken into account, the average return is -0.0047 for the S-M-A rules, -0.0078 for the D-M-A rules, and -0.0298 for the T-R-B rules.

Table 6. Annualized returns of the three rules for Taiwan stock market

Rules	2009-2018		2009-2013		2014-2018	
	No Cost	Cost	No Cost	Cost	No Cost	Cost
Buy-Hold	0.0780	0.0773	0.1340	0.1327	0.0246	0.0234
S-M-A						
20-day	0.0401	0.0059	0.0933	0.0564	-0.0071	-0.0380
50-day	0.0229	-0.0002	0.0846	0.0616	-0.0312	-0.0537
100-day	0.0090	-0.0062	0.0139	-0.0005	0.0022	-0.0130
150-day	0.0153	0.0041	0.0167	0.0069	-0.0046	-0.0174
200-day	-0.0007	-0.0129	0.0014	-0.0106	-0.0063	-0.0179
250-day	0.0138	0.0055	0.0078	0.0005	0.0186	0.0115
Average	0.0167	-0.0007	0.0363	0.0191	-0.0047	-0.0214
D-M-A						
20-2	0.0394	0.0070	0.0910	0.0555	-0.0064	-0.0351
50-2	0.0282	0.0085	0.0848	0.0669	-0.0196	-0.0401
100-10	-0.0092	-0.0196	0.0050	-0.0046	-0.0289	-0.0402
150-10	0.0022	-0.0054	0.0046	-0.0027	-0.0185	-0.0265
200-10	0.0085	0.0032	0.0146	0.0096	0.0048	0.0001
250-10	0.0040	-0.0007	-0.0084	-0.0134	0.0216	0.0181
Average	0.0122	-0.0012	0.0319	0.0185	-0.0078	-0.0206
T-R-B						
20-day	0.0490	0.0392	0.1103	0.0970	-0.0007	-0.0065
50-day	0.0140	0.0086	0.0587	0.0522	-0.0311	-0.0345
100-day	-0.0175	-0.0204	-0.0120	-0.0146	-0.0252	-0.0274
150-day	-0.0024	-0.0041	0.0026	0.0012	-0.0292	-0.0315
200-day	-0.0033	-0.0050	0.0128	0.0113	-0.0463	-0.0485
250-day	-0.0145	-0.0162	-0.0098	-0.0113	-0.0463	-0.0485
Average	0.0042	0.0004	0.0271	0.0226	-0.0298	-0.0328

Note: Buy-Hold is the buy-and-hold strategy. “No Cost” and “Cost” indicate that the trading costs are not included and included, respectively

5.2. Comparison of average returns between the four markets

Table 7 shows the average annualized returns for the four markets. Relatively speaking, the Hong Kong market performs better than the other markets with the T-R-B rules and over the 2014-2018 subperiod. For example, the average return from the T-R-B rules with trading costs is 0.0345 for the 2009-2018 entire period, 0.0487 for the 2009-2013 subperiod, and 0.0067 for the 2014-2018 subperiod. In addition, the average return over the 2014-2018 subperiod with no trading costs is 0.0360 from the S-M-A rules, 0.0469 from the D-M-A rules, and 0.0088 from the T-R-B rules. On the other hand, the Singapore market performs slightly better the other markets with the two moving average rules, and over the 2009-2018 period and the 2009-2013 subperiod. For example, without trading costs, the S-M-A rules result in an average return of 0.0218 over the 2009-2018 period and 0.0370 over the 2009-2013 subperiod.

These technical rules are not effective at all in the two markets of Korea and Taiwan. With only one exception (i.e., the T-R-B rule over the 2009-2013 subperiod), the average returns from the Korea market with trading costs are all negative over the three periods. For example, over the 2009-2018 entire period, the average return is -0.0230 from the S-M-A rules, -0.0206 from the D-M-A rules, and -0.0059 from the T-R-B rules. On the other hand, with and without trading costs, the average returns from the Taiwan market are all negative over the 2014-2018 subperiod from the three technical rules.

Table 7. Average annualized returns of the three rules for the four stock markets

Rules	2009-2018		2009-2013		2014-2018	
	No Cost	Cost	No Cost	Cost	No Cost	Cost
S-M-A						
Hong Kong	0.0207	0.0130	0.0200	-0.0152	0.0360	0.0075
Korea	0.0057	-0.0230	0.0204	-0.0101	0.0020	-0.0220
Singapore	0.0218	0.0088	0.0370	0.0227	0.0060	-0.0056
Taiwan	0.0167	-0.0007	0.0363	0.0191	-0.0047	-0.0214
D-M-A						
Hong Kong	0.0216	-0.0029	0.0073	-0.0201	0.0469	0.0268
Korea	0.0007	-0.0206	-0.0009	-0.0245	0.0117	-0.0056
Singapore	0.0137	0.0037	0.0159	0.0046	0.0120	0.0034
Taiwan	0.0122	-0.0012	0.0319	0.0185	-0.0078	-0.0206
T-R-B						
Hong Kong	0.0350	0.0345	0.0498	0.0487	0.0088	0.0067
Korea	0.0008	-0.0059	0.0156	0.0082	-0.0164	-0.0224
Singapore	0.0106	0.0080	0.0234	0.0199	-0.0063	-0.0083
Taiwan	0.0042	0.0004	0.0271	0.0226	-0.0298	-0.0328

Note: "No Cost" and "Cost" indicate that the trading costs are excluded and included, respectively

6. Conclusion and future research

The implication of the efficient market hypothesis (EMH) is that it is not possible to make abnormal returns in an efficient market with any investment tools or strategies. That said, this study investigates the effectiveness of three popular technical trading rules, using buy-and-hold (B-H) strategy as the benchmark, in the four Asian stock markets of Hong Kong, Korea, Singapore, and Taiwan after the 2008 financial crisis. With a few minor exceptions in Hong Kong and Singapore, our results show that, in general, none of the three technical rules perform better than the B-H strategies in any of the four stock markets. However, a rather ironic phenomenon is that the three rules perform slightly better in the two developed markets of Hong Kong and Singapore than in the two emerging markets of Korea and Taiwan. In other words, the two emerging markets are relatively more efficient than the two developed markets. All in all, given that excess returns are not possible, we conclude that the four stock markets are efficient.

There are two explanations for the efficiency of the four stock markets. First and foremost, the EMH claims that, in an efficient market, security prices at any point in time fully reflect all relevant information. In the past, investors needed time to collect and analyze information, and then to take buy or sell actions thereafter. However, over the past 20 years or so, the fact that state-of-the-art computer technology can execute all these in a matter of less than a second has helped to enhance the validity of the EMH claim. Second, in the aftermath of the 1997 and 2008 crises, a series of improvement and reform measures were implemented in these four markets — those derivative markets in particular. For example, to avoid the turmoil that wreaked havoc on over-the-counter derivatives markets during the 2008 crisis, market regulators of these four Asian dragons have set up task forces (Cookson, 2010) to improve the efficiency and transparency of their derivatives markets. Undoubtedly, such measures have helped to bolster the efficiency of their stock markets.

In 2013, the Royal Swedish Academy of Sciences conferred the Nobel Prize in Economics upon Fama to recognize the importance of the EMH in explaining the dynamics of security prices. The Academy stated that his findings not only had a profound impact on subsequent research but also changed market practice. Given the above results, we believe that the EMH claim remains alive and well in these four Asian stock markets. In actual practice, many large companies operating in these four markets typically turn to banks for financing. Hence, an important implication of this study is that, given the efficiency of the four markets, these companies should instead step up the use of the stock markets to raise the needed funds, which is more likely to lower their cost of financing.

Much related research work remains to be done. In one direction, it would be nice to examine some other technical rules (e.g., the Bollinger bands, candlestick charting, the Elliott wave, the Fibonacci retracement, head and shoulders pattern, the relative strength index) to find out if the four stock markets remain efficient. In another direction, it would be interesting to explore the effect of the COVID-19 pandemic on their efficiency. That is, would these stock markets remain efficient if the 2019-2021 data were included in this study?

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