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Intertemporal profitability and the stability of technical analysis: evidences from the Hong Kong stock exchange

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This study investigates the impact of market integration on the profitability of two simple and popular technical trading rules, the Simple Moving Average (SMA) and the Trading Range Break (TRB) in Hong Kong. Using data from 1972 to 2006, we find that the SMA (1, 50) consistently outperforms the market before the integration of stock exchanges in 1986. Under the (1, 50) rule, a variable length moving average performs better than the fixed length moving average rule by 2.5 to 5% (annual) before transaction costs because it includes the information of the first 9 days into investors' decision. The results are robust to the out of sample tests for the validity of the profitability of the trading rules. The returns of the trading range break rules are insignificant over the 35-year span. Our results support the conjecture that stock market integration may lead to better information efficiency. The findings of significant pre-1986 profits and insignificant post-1986 profits, contradict previous findings that returns are predictable in Hong Kong, suggesting that the Hong Kong stock market may be weak-form efficient after 1986. Overall, our results suggest that technical analysis matters for asset pricing.

I. Introduction

In his seminal paper, Fama (1970) classifies the Efficient Market Hypothesis (EMH) into three forms, weak-form, semi-strong form and strong form, according to the types of information to be reflected. The weak-form market efficiency hypothesis states that today's security prices fully reflect all information contained in historical security prices. That means we cannot find any pattern in security prices or security prices have no 'memory'. The hypothesis is concerned with the forecasting power of past returns. Therefore, the use of today's stock price as a forecast of tomorrow's stock price is as likely to be as good as any forecasting tool. This implies that, if the market is weak-form efficient, no investor can earn excess risk-adjusted returns by developing trading rules based on historical prices or return information.

Lo *et al*. (2000) suggest that some technical indicators are informative and maybe of practical value. Menkhoff and Taylor (2007), Allen and

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Taylor (1990), Taylor and Allen (1992) and Levich and Thomas (1993) provide evidence that technical analyses matter to financial markets. As one of the most volatile stock markets in the world, the Hong Kong stock market provides an ample number of profitable opportunities to investors. Should investors be able to generate profits with technical trading strategies in the stock market? Does the market integration of 1986 matter for profitability of technical trading rules? Does the market integration increase information efficiency and/or market efficiency? These questions are important, but as yet unanswered.

This study investigates the impact of the profitability of two simple and popular technical trading rules, the Simple Moving Average (SMA) and the Trading Range Break (TRB) before and after market integration. Using the data from the Hong Kong stock market from 1972 to 2006, we find that, the SMA(1, 50) – buying (selling) when the 1-day moving average rises above (falls below) the 50-day moving average – consistently outperforms the market before market integration took place in 1986. Under the (1, 50) rule, the variable length moving average performs better than the fixed length moving average rule by 2.5 to 5% (annual) before transaction costs because it includes the information from the first 9 days into investors' decisions. The results are robust to the out of sample tests for the validity of the profitability of the trading rules. The returns of the trading range break rules are insignificant over the 35-year span. Our results support the conjecture that stock market integration may lead to better information efficiency.

> The Hong Kong Exchange and Clearing Limited (HKEX) is one of the fastest growing emerging markets, ranked seventh in the world and second in Asia in terms of market capitalization by the end of 2006. However, there are only a few studies on the profitability of technical trading strategies in the HKEX (http://www.hkex.com.hk/news/hkexnews/0701122news.xls).
> Notable exceptions are Bessembinder and Chan (1995), and Coutts and Cheung (2000). These studies have two distinct features – they both use linear models and find profits from the trading strategies after transaction costs. We differentiate our model from Bessembinder and Chan (1995) and Coutts and Cheung (2000) by employing a linear model with the out of sample test to minimize the selection bias. We use the out of sample test to avoid the well-known data-snooping problem. According to Lo and MacKinlay (1990), the more scrutiny a data set receives, the more likely that interesting spurious patterns will be uncovered.[1] To avoid this problem, we use the out of sample testing technique. By using the out of sample test, which applies trading rules from one period to another period, we can compute test statistics from a different data period. Thus, the interesting patterns found are less likely to be affected by the data-snooping biases. The results of the out of sample test would then provide valuable insight into the results of the traditional tests.

The findings of significant pre-1986 profits and insignificant post-1986 profits contradict some of the previous findings that returns are predictable in Hong Kong. Our results suggest that the Hong Kong stock market may be weak-form efficient after 1986. We present our results with two robustness tests. First, we find that the abnormally high pre-1986 average returns from the SMA and TRB rules can only be partially explained by the positive first order autocorrelation in the Hong Kong stock market. Second, we find that the average returns are still very high after transaction costs.

Our major contribution is that we find significant profitability for some of the moving average trading strategies but not in any trading range break rules before 1986.

The trading profit is insignificant in the subperiods after 1986, where the integration of four stock exchanges took place. The integration of stock exchanges, together with the commencement of a computer-assisted order matching system, eventually leads to a more efficient dissemination of information. Market integration increases information efficiency by enhancing market liquidity and lowering the cost of capital. Padilla and Pagano (2006) examine the economic gains of stock exchange integration (from 2000 to 2003) resulting in the formation of Euronext. They find that the integration is associated with a higher transaction volume, smaller bid-ask spread and lower volatility after the integration. Stulz (1999) states that in equilibrium,

[1] According to Lo and MacKinlay (1990), the data-snooping biases occur if test statistics are affected by the empirical relations uncovered in the same data that test statistics are applied. The new trading rules may exhibit apparently significant forecast power simply because the same data are used to test the new trading rules. In such a case, researchers may mistakenly conclude significant trading rule profits because of the data-snooping biases.

financial market integration should be associated with lower risk premiums, expected returns on equity and cost of capital.[2] Our findings may be important for future financial market integration, a prominent agenda in Europe (Jappelli and Pagano 2008). Our findings shed light on technical analysis, market integration and information efficiency by employing out of sample tests before and after the major market integration of the Hong Kong stock market.

This article is organized as follows. The next section discusses hypothesis development. Section III presents the data and methodology. Section IV reports the main results. Section V concludes the article.

II. Hypothesis Development

The benefit of trading strategies has been studied in both developed and developing countries. In US, early studies show that filter rules can earn small abnormal returns, but they vanish after taking into account the transaction costs (Alexander, 1961, 1964; Fama and Blume, 1966; Sweeney, 1988). Neftci (1991) evaluates *ad hoc* trading rules on the Dow–Jones Index and finds that few of the rules generate well-defined techniques of forecasting. However, Brock *et al.* (1992) use a long period of data, over 100 years, to test two technical trading rules (moving average and trading range break) via bootstrapping. They find that these trading rules contain predictive ability. However, Bessembinder and Chan (1998) document that the inclusion of trading costs and adjustments for nonsynchronous trading, eliminate the technical trading rule profits in US, but not the economic significance of the Brock *et al.*'s study. Blume *et al.* (1994) are able to establish profitable trading rules with trading volumes. They find that traders who use information contained in market statistics do better than traders who do not.

In UK, Hudson *et al.* (1996) replicate Brock *et al.*'s (1992) research and find that, in the UK market, the trading rules have predictive ability if a sufficiently long series of stock indexes are considered. However, excess returns vanish in the presence of trading costs. Mills (1997) also reaches the same results as Hudson *et al.* (1996). Isakov and Hollistein (1998) find that transaction costs eliminate technical trading profits in the Swiss stock market.

In Asia, Bessembinder and Chan (1995) replicate Brock *et al.*'s (1992) study in six Asian markets. They find that the trading rules are quite successful in the emerging markets of Malaysia, Thailand and Taiwan but have less explanatory power in more developed markets, such as Hong Kong and Japan. Ratner and Leal (1999) examines the predictability of the Variable Length Moving Average (VMA) trading rule in 10 emerging Latin American and Asia stock markets (from 1982 to 1995) and find that the VMA trading rule may be profitable in Taiwan, Thailand and Mexico. Coutts and Cheung (2000) study the trading rule profitability in the Hong Kong stock market and find that the rules fail to provide positive abnormal returns after transaction costs.

The profitability of trading strategies may be associated with irregularities in the markets. For example, in US, studies find that there is a positive autocorrelation of weekly returns on a portfolio of NYSE stocks (Lo and MacKinlay, 1988; Conrad and Kaul, 1989) and negative autocorrelation on individual stocks (Fama and French, 1988; Poterba and Summers, 1988; Lehmann, 1990). Jegadeesh (1990) finds negative serial correlation for lags up to 2 months and positive correlation for longer lags. Other market inefficiencies are also reported. They are, namely, the market overreaction (De Bondt and Thaler, 1985, 1987; Chopra *et al.*, 1992), the January effect (Rozeff and Kinney, 1976; Ritter and Chopra, 1989), the Monthly effect (Ariel, 1987; Lakonishok and Smidt, 1988), the Weekend effect (French, 1980; Keim and Stambaugh, 1984) and the holiday effect (Lakonishok and Smidt, 1988; Ariel, 1990). These indicate that stock prices do not necessarily follow random walk in US. The findings of the literature seem to show that the daily and weekly stock returns can be predicted from past stock returns and financial variables.

In Europe, evidences of market inefficiency are also found. For example, autocorrelation is found in the Swedish stock market (Frennberg and Hansson, 1993), seasonality and weekend effect are found in the London Stock Exchange (Jaffe and Westerfield, 1985; Reinganum and Shapiro, 1987), and weak-form inefficiency is found in the Athens Stock Exchange (Koutmos *et al.*, 1993; Spyrou, 1998; Kavussanos and Dockery, 2001).

The Asian stock markets studies show that the nontrivial first order auto-corrections are found in six stock markets, namely, Hong Kong, Japan, Korea, Malaysia, Thailand and Taiwan

[2] While cross-border integration may be subject to home equity bias (Tesar and Werner, 1995; Lewis, 1999), our conjecture should be free of the home equity bias, i.e. local investors diversify sufficiently into the integrated market.

(Bailey *et al*., 1990; Pan *et al*., 1991; Bessembinder and Chan, 1995). In addition, the January effect (Gultekin and Gultekin, 1983; Kato and Schallheim, 1985), the Weekend effect (Ho, 1990; Lee *et al*., 1990; Wong *et al*., 1992; Ho and Cheung, 1994), and the Chinese New Year effect (McGuinness, 2005) are found in various Asian countries (for example, Japan, Korea, Malaysia, Thailand and Taiwan).

In sum, the evidence from runs tests and random walk tests suggests that the US market is weak-form efficient over a short horizon, but ambiguous over longer horizons. However, findings related to trading rules based on technical analysis suggest that stock returns are predictable from past returns. This evidence is contrary to that found in random walk tests and seems not to support the weak-form efficiency hypothesis for the US market. In Europe, the evidence suggests that excess returns can be generated by trading rules, but they vanish after transaction costs. In Asian markets, however, test results indicate that most of the major markets are weak-form inefficient in both individual stocks and portfolios of stock. In Hong Kong, studies find positive abnormal returns using the two simple trading rules, but they vanished after transaction costs.

III. Data and Methodology

Data

We use the daily closing value of Hang Seng Index (HSI) in our study. The data period is 35 years from 1 January 1972 to 31 December 2006. The data comes from DataStream Ltd.

In order to investigate the consistency of the trading strategies, we subdivide the data into four subperiods. The first subperiod is from 1 January 1972 to 31 December 1978 (7 years). The second subperiod is from 1 January 1979 to 31 December 1985 (7 years). The third subperiod is from 1 January 1986 to 31 December 1995 (10 years) and the fourth and final subperiod is from 1 January 1996 to 31 December 2006 (11 years).

To subdivide the data set, we use 1986, the year where four Hong Kong stock exchanges unified into one stock exchange, the Stock Exchange of Hong Kong, as the cutoff year. We then further subdivide the two periods into two equal subperiods.

One problem with the HSI is that it does not adjust for dividend payment. Therefore, it does not contain information about the payment of dividends and may cause bias in the study. However, Mills and Coutts (1995), after reviewing literature concerning dividends, conclude that the bias in excluding dividends is minimal, a conclusion confirmed by Draper and Paudyal (1997).

The HSI is a value weighted index composed of 33 actively traded 'blue chip' stocks. Since the constitute stocks on the HSI are very actively traded stocks, there is no 'thin trading' and 'nonsynchronous' trading problem in the index (Cheung and Ho, 1991). In addition, the HSI reflects a broad industrial base and represents more than 70% of the market value of the HKEX. Therefore, it is an ideal index for investigating the validity and applicability of trading rules.

Methodology

In technical analysis, there are many techniques designed to identify and exploit patterns in historical prices. In this article, we focus on SMA and TRB rules because the buy and sell signals generated from the two trading rules are unambiguous. Other technical trading rules, such as 'head and shoulders' patterns and Elliot Waves, cannot be tested properly because they require trader interpretation which leads to ambiguous buy and sell signals. Another reason for using the SMA and TRB rules is because we want to compare our results with previous studies. Therefore, in our study, we examine the same set of trading rules, SMA and TRB rules, used by Brock *et al.* (1992) and Bessembinder and Chan (1995).

SMA trading rule. The SMA can be constructed by summing the data for a specific period (e.g. 10 days) and taking the average. It is called the *n*-day moving average. If the moving average is 20 days or below, it is regarded as a short-term moving average. If it is between 20 and 50 days, it is a medium-term moving average. If it is greater than 50 days, it is a long-term moving average. The rule is that if the short-term moving average breaks the medium or long-term moving average from below, it sends out a buying signal. This is because, when short-term moving average breaks from below, the market must be rising. It is expected that the market will keep on rising for a while. The shorter moving average tends to have larger values than the longer average, requiring a long position. Thus, it is time to buy at the beginning of the rising market trend. A selling signal emerges when the short-term moving average breaks the medium or long-term moving average from above. It signals that the market is falling. When the market is falling, the shorter average tends to have lower values than the longer average, requiring a short position.

The SMA trading rules are further divided into Variable Length Moving Average (VMA) rules and Fixed Length Moving Average (FMA) rules. For the VMA rules, buy (sell) signals are generated when the short-term moving average exceeds (falls below) the long-term moving average by a pre-specified percentage band. If it is inside the bandwidth, no signal will be generated. If the band is 0%, the VMA rules classify every day into either a buy or sell day. The use of bandwidth is to avoid the emission of false signals when the short-term and long-term moving averages are close to each other.

The FMA rules use the same set of rules as VMA rules to generate buy (sell) signals. However, the FMA rules further assume that returns should be different for a few days after the signals are generated. Thus, if signals are generated, the FMA rules require investors to stay in the same position (i.e. either buy or sell) for a fixed number of days, 10 days in this study. Other signals generated during this 10-day period are ignored. When the 10-day period passes, the FMA rules start to react to new signals.

For each of the VMA and FMA rule groups, this study evaluates the five variations of the rules, (1, 50), (1, 150), (1, 200), (2, 200) and (5, 150), where the first number in the parentheses denotes the number of days for the short-term moving average and the second number denotes the number of days for the long-term moving average. In addition, each rule is evaluated with the bands of 0, 1, 2 and 3%, making for 20 individual rules in total for each rule group.

The buy and sell signals are generated as follows:

$$\sum R_{i,t}/S > (1+X)\sum R_{i,t-1}/L = \text{Buy} \tag{1}$$

and

$$\sum R_{i,t}/S < (1+X)\sum R_{i,t-1}/L = \text{Sell} \tag{2}$$

where

$$R_{i,t} = (I_{i,t} - I_{i,t-1})/I_{i,t-1} \quad \text{and} \quad X = 0, 1, 2 \text{ or } 3\%$$

$R_{i,t}$ is the daily return of HSI in period S (1, 2 or 5 days); $R_{i,t-1}$ is the daily return of HSI over period L (50, 150 and 200 days); $I_{i,t}$ is the closing HSI at t; X is the pre-specified percentage band. i represents the trading rules (1, 50), (1, 150), (1, 200), (2, 200) and (5, 150). Σ is the summation operator. In this article, we use the out of sample simulation to investigate whether the trading rule works in general and also to identify which combination(s) works best in particular. The problem with the traditional approach of simulating profit from historical periods and choosing one best SMA is that it is subjected to selection bias. If enough combinations are tried, at least one SMA is likely to work simply by chance. The advantage of using the out of sample simulations is that the results are not contaminated by selection bias. We follow a two-step procedure to select optimal SMAs and their profits. We start by searching for the most profitable SMA among the 5 possible combinations of SMAs within a particular bandwidth for Year 1 of our sample. We then use that optimal combination (e.g. 1 and 50 day moving averages or (1, 50, 0) trading rule) to simulate trading in Year 2. The simulation is done by applying the trading rule (e.g. (1, 50, 0)) in Year 1 to Year 2 HSI data and then computing and recording the returns generated. The next step is to re-optimize by searching for the most profitable SMA for Years 1 and 2 combined. We then use the new optimal combination (e.g. 2 and 200 days moving averages) to simulate and record returns for Year 3. This sequential searching for the optimal SMA and simulation of return is continued through the end of the sample period.

We have 37 years of data (1970–2006, including the 200 observations for Year 1) and 35 years (1972–2006) of out of sample daily returns simulations from following a moving average trading strategy. We measure returns on stock prices as the difference between closing price on day t (P_t) and the closing price on day $t-1$ (P_{t-1}) divided by the closing price on day $t-1$ (P_{t-1}). This statistic is then multiplied by 1 if the trading rule specifies a long position and multiplied by –1 if the rule requires a short position. To determine whether the simple moving average trading rule generates abnormal returns requires a risk-adjusted measure of return to compare with alternative investments. We use the return from the buy-and-hold strategy for the HSI as our benchmark measure.

TRB trading rule. In contrast to the simple moving average rule, the second trading rule, the TRB, initiates a sell (buy) signal if the security price falls below (rises above) some pre-defined support (resistance) level, the highest (lowest) price of the security in the previous period. The time periods are 50, 150 and 200 days and the bands are 0, 1, 2 and 3%, respectively. The 10-day cumulative returns after the signals will be reported. The TRB rule works similarly to the SMA rule by identifying the trend in price series. An upward (downward) trend is identified when the current price is equal to or greater (less) than the maximum (minimum) price over the period of the pre-specified length. A long (short) position is taken when the stock price breaks the maximum (minimum) barrier. The logic for this rule is that when the current price reaches the previous peak (low), a great deal of selling (buying) pressure arises because many people would like to sell (buy) at the peak (trough). However, if the price exceeds the previous peak (trough), it indicates that the upward (downward) trend has initiated. The formulas for the buy and sell signals are as follows:

$$P_t > (1+X)\max(P_{t-1},\ldots,P_{t-m}) = \text{Buy} \qquad (3)$$

$$P_t < (1+X)\min(P_{t-1},\ldots,P_{t-m}) = \text{Sell} \qquad (4)$$

where P_t is the closing HSI closing at t; m is the time period we selected (50, 150 and 200 days); X is the percentage band, 0, 1, 2 and 3%, respectively; $\max(P_{t-1},\ldots,P_{t-m})$ is the maximization operator for the HSI series; $\min(P_{t-1},\ldots,P_{t-m})$ is the minimization operator for the HSI series.

This study evaluates the TRB rules where recent maximums and minimums are defined as the extreme observations over the time period 50, 150 and 200 days, respectively. In addition, each rule is evaluated with the bands of 0, 1, 2 and 3%, making for 12 rules in total. Similar to the SMA trading rules, the benchmark for evaluating the abnormal returns for the TRB trading rule is the return of the buy-and-hold strategy for the HSI.

The out of sample test is also carried out for the TRB rules on three different time periods. The best time period, 50, 150 or 200 days, is chosen from one time period and applies to next year's data. The average simulated returns for the entire 35 years will be collected and tested using the same procedure as in SMA strategy.

IV. Empirical Results

Sample statistics

Table 1 contains summary statistics for the entire sample series and the four subperiods for both mean

Table 1. Descriptive statistic[a]

Raw return	Full sample (72–06)	1st subperiod (72–78)	2nd subperiod (79–85)	3rd subperiod (86–95)	4th subperiod (96–06)
Panel A: Daily return					
N	8648	1729	1726	2477	2716
Mean	0.000648	0.000503	0.000911	0.000851	0.000389
SD	0.018735	0.024056	0.018873	0.016497	0.016581
Skewness	−0.640909	0.532190	−0.326429	−4.584761	0.453207
Kurtosis	20.784503	5.653932	2.894608	83.468018	13.017075
Serial correlations					
$\rho(1)$	**0.0820***	**0.1609***	**0.0473****	**0.0623***	0.0255
$\rho(2)$	−0.0171	−0.0099	0.0126	−0.0220	**−0.0455***
$\rho(3)$	−0.0040	−0.0123	0.0010	−0.0033	−0.0025
$\rho(4)$	0.0066	0.0099	0.0031	0.0060	0.0044
$\rho(5)$	−0.0015	0.0072	0.0015	−0.0029	−0.0054
Panel B: 10-day return					
N	864	172	172	247	271
Mean	0.000644	0.000519	0.000905	0.000843	0.000371
SD	0.006586	0.009256	0.006748	0.005678	0.005343
Skewness	−0.421055	0.149345	−0.689621	−2.583195	−1.296585
Kurtosis	4.360649	2.199964	0.736767	20.025099	12.434681
Serial correlations					
$\rho(1)$	**0.1267***	**0.2245***	**0.0473***	**0.0595***	**0.0824***
$\rho(2)$	**−0.0139****	**0.0368***	**−0.0659***	**−0.0864***	**0.0201***
$\rho(3)$	−0.0080	−0.0065	−0.0069	−0.0117**	0.0022
$\rho(4)$	−0.0019	−0.0100	0.0036	0.0069	−0.0015
$\rho(5)$	0.0022	0.0140	0.0018	−0.0027	0.0004

Notes: [a]Results are shown for the full period and four nonoverlapping subperiods. Returns are measured as percentage differences of the HSI, 10-day return is the average of 10 nonoverlapping daily returns. N is the number of observations. $\rho(i)$ is the estimated i days lag autocorrelation. Figures marked in bold are at least 10% significant. * and ** represent significance at the 1 and 5% levels, respectively.

daily returns and 10-day mean daily returns on the HSI. The returns are calculated as raw returns of HSI.[3] Panels A and B report the results of the Mean Daily Returns (MDRs) and the 10-day Mean Daily Returns (10-day MDRs), respectively. The SDs (volatility) of the MDRs are substantially higher than the 10-day MDRs for all periods. The volatilities of both sets of mean daily returns are quite stable across subperiods except the first subperiods (1972–1978), which are substantially higher than the other three subperiods and the full sample periods. The skewness of the MDRs for the full sample period, and the second and third subperiods' returns are significantly skewed to the left, and the first and four subperiods returns significantly skewed to the right. Whereas the skewness of the 10-day MDRs for the full sample period, and the second, third and fourth subperiods' returns are significantly skewed to the left, and the first subperiod returns significantly skewed to the right. The skewness of the 10-day MDRs is, in general, slightly lower than the MDRs. The skewness in the third sub-period (1986–1995) of both mean daily returns are exceptionally high and negative (−4.585 for MDRs and −2.5832 for 10-day MDRs, respectively), which causes the overall skewness to be negative in both sets of MDRs (skewnesses are −0.6409 and −0.4211, respectively). The high negative skewness is probably due to the sharp stock market drop on 5 June 1989 caused by the June 4th event. In general, the MDRs and 10-day MDRs are significantly skewed to the left.

In addition, the MDRs are highly leptokurtic (kurtosis is 20.7845) while the 10-day MDRs are just lightly leptokurtic (kurtosis is 4.3606). The high kurtosis in the MDRs is evidenced in all four sub-periods except the second sub-period (1979–1985). To check whether the kurtosis is caused by just a few outliners, 16 outliner returns[4] are deleted from the data set, and the skewness and kurtosis are recomputed for the reduced daily mean return series. The skewness and kurtosis for the reduced entire sample and the four subperiods are similar to the full sample. In general, we can infer that the nonnormality is not caused by the outliners. We also use log returns to compute the skewness and kurtosis and find that they are similar to those of the raw returns. Since we are doing out of sample tests for trading rules, we need to use continuous daily returns. Therefore, we choose to use raw returns and include the outliners in the sample periods.

The serial correlations are generally very small except in the first subperiod (1972–1978) for both the MDRs. The two sets of returns exhibit very similar serial correlation patterns in the first five serial correlations. They both have significant positive first order serial correlation, $\rho(1)$. The higher order (second to five) serial correlations are mostly insignificant. The second and third order serial correlations are, in general, negative and insignificant while the fourth and fifth order serial correlations are insignificant and very small.

Traditional and out of sample tests

In this section we report the empirical results for the traditional and out of sample test on the two trading strategies, SMA and TRB. We will report the finding of SMA in the first and second subsections (i.e. Sections 'VMA strategy' and 'FMA strategy') and the results of TRB in the third subsection (TRB strategy). We are testing two different strategies under SMA, namely VMA strategy and FMA strategy.

VMA strategy. Table 2 contains the results of the traditional test of VMA strategy over the full sample period and the four subperiods. To save space, we only report the results for bandwidth 0%. Column two presents the trading rules employed in the study. These rules differ from each other by the length of the short and long moving average periods, and by the width of the band. For example (1, 50, 0) indicates that the short period is 1 day, the long period is 50 days, and the bandwidth is 0%. Whereas columns three and four report the number of buy and sell days generated by VMA. On average, for all 20 trading rules, there are 63.66% more buy days (4, 963.30) than sell days (3, 032.70). It is consistent with the upward-market trend of HSI during the sample period. Buy and sell average returns are reported separately in columns five and six. In Panel A, all buy returns are positive with only the (1, 50) trading rule returns statistically larger than the unconditional mean daily return (MDR at 0.0648% daily or 16.20% annually), at the 5% significant level. The average 1-day buy return is 0.09% (about 22.50% per year), which is close to those reported by Bessembinder and

[3] The log differences of HSI are also calculated. Since the two results are very similar, we only report the results of the raw returns here.

[4] The dates deleted are 27 November 1974 (Hong Kong dollars are allowed to float due to the oil crisis), 12 and 13 August 1982 (property market crash), 26 October 1987 (Black Monday crash), 5 June 1989 (June 4th event), 23 and 24 October 1997 (Asia financial crisis and property market collapse), 2 February 1998 (property downturn) and 11 September 2001 (9/11 terrorist attack).

Table 2. VMA trading strategy[a]

Period	Test	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy–sell
Panel A: Full sample								
1972–2006	(1, 50, 0)	5241	3249	0.14%	−0.06%	0.54	0.52	0.21%
				2.30**	−3.34*			4.89*
	(1, 150, 0)	5538	3094	0.10%	0.00%	0.54	0.51	0.10%
				1.10	−1.58			2.33**
	(1, 200, 0)	5345	2972	0.08%	0.01%	0.53	0.51	0.07%
				0.41	−1.32			1.59
	Average	4963.3	3,032.70	0.09%	0.00%			0.09%
				0.81	−1.62			2.12**
Panel B: Four subperiods								
1972–1978	(1, 50, 0)	799	771	0.27%	−0.21%	0.53	0.56	0.48%
				2.04**	−2.39**			3.84*
	(1, 150, 0)	963	749	0.16%	−0.08%	0.52	0.54	0.24%
				1.06	−1.21			2.01**
	(1, 200, 0)	723	674	0.04%	−0.07%	0.50	0.55	0.11%
				−0.08	−1.09			0.95
1979–1985	(1, 50, 0)	1098	620	0.17%	−0.06%	0.55	0.52	0.23%
				1.11	−1.73***			2.47**
	(1, 150, 0)	1080	562	0.15%	−0.02%	0.54	0.50	0.17%
				0.77	−1.25			1.74***
	(1, 200, 0)	1045	660	0.12%	0.03%	0.54	0.49	0.09%
				0.41	−0.72			0.98
1986–1995	(1, 50, 0)	1714	749	0.12%	0.01%	0.54	0.49	0.11%
				0.66	−1.15			1.57
	(1, 150, 0)	1780	657	0.07%	0.13%	0.53	0.47	−0.05%
				−0.21	0.55			−0.67
	(1, 200, 0)	1777	658	0.08%	0.11%	0.54	0.47	−0.04%
				−0.13	0.40			−0.47
1996–2006	(1, 50, 0)	1570	1101	0.07%	−0.02%	0.53	0.51	0.09%
				0.64	−0.95			1.38
	(1, 150, 0)	1545	1042	0.07%	−0.01%	0.54	0.51	0.08%
				0.59	−0.83			1.22
	(1, 200, 0)	1616	959	0.07%	−0.02%	0.54	0.52	0.09%
				0.66	−0.95			1.38

Notes: [a]The test period is from 1972 to 2006. Rules are classified as short, long and band. Short represents the length of the short moving average and long represents the length of the long moving averages. Band is the percentage difference between the long and short moving averages required to generate a signal. 'N(buy)' and 'N(sell)' represent the total number of buy and sell days generated within the period. Numbers below the percentage return are the corresponding t-ratios. The t-value is testing the difference of the mean buy and sell returns from the unconditional mean return, and the buy–sell from zero. Buy and Sell are 1-day lag average buy and sell returns, respectively. 'Buy > 0' and 'Sell > 0' measures the probability of getting a positive return in a buy and sell day. *, ** and *** represent significance at the 1, 5 and 10% levels, respectively.

Chan (1995) (0.084%). On the buy side, the (1, 50) trading rules are the best performing trading rules with the highest average returns and t-values among all reported trading rules.

On the sell side, all sell returns are mostly positive except the (1, 50) trading rules. The returns of the (1, 50) trading rule are statistically larger than the unconditional MDR at the 5% significant level. The average 1-day sell return is 0%, which is slightly lower than those of Bessembinder and Chan (1995) (0.03%). On the sell side, again, the trading rules (1, 50) are the best performing trading rules with the highest average returns and t-values among all reported trading rules.[5]

When we perform tests with 1-day lag returns, we find that the average buy and sell return figures are slightly higher, but very close to those of Bessembinder and Chan (1995). Our 1-day lag average buy and sell returns are 0.09% (22.50% annually) and 0.01% (2.50% annually), respectively while their returns are 0.079% (19.75% annually) and −0.041% (−10.25% annually), respectively. The slight differences on both 0-day and 1-day lag returns may be caused by the difference in test

[5] The negative returns under the (1, 50) trading rules turn positive when a short selling strategy is used. Therefore, the (1, 50) trading rules are considered to be the best.

periods employed. We use a much longer test period (1972–2006, 35 years), 18 years longer than those used by Bessembinder and Chan (1995) (1975–1991, 17 years).

Columns seven and eight present the probability of having a net gain in both buy and sell days. The probability of having a net gain ranges narrowly from 50 to 55% with most of the average buy and sell gain percentages come very close to each other. With these slightly above the average probability rate, we can infer that the significant returns on buy and sell signals are not likely due to the inclusion of the 16 extreme observations. The ninth and last column shows the difference between the mean daily buy and sell returns. The buy–sell differences are positive and significantly different from zero for the full sample period for only three strategies, $(1, 50, 0)$, $(1, 50, 1)$ and $(1, 150, 0)$ at the 5% confidence level. For the four subperiods (Table 2, Panel B), we only observe similar results in the first subperiod (1972–1978). For the second subperiod (1979–1985), only the buy–sell differences of the $(1, 50)$ trading rules are positive and significantly different from zero at the 5% level. For the last two subperiods (1986–1995 and 1996–2006), no returns of trading rules are positive and significantly different from zero at the 5% confidence level. The full sample buy–sell difference ranges from 0.04% daily (12.50% annually) to 0.22% daily (55% annually). The average buy–sell difference for the 20 trading rules is positive (0.09% daily and 22.50% annually) and significantly different from zero at the 5% level of significance. This rejects the null hypothesis that the mean daily buy return is the same as the mean daily sell return. But it should be noted that the significant average buy–sell return is mainly caused by the significant buy–sell returns from two groups of trading rules, the $(1, 50)$ and $(1, 150)$ rules. In addition, we also observed that the introduction of bandwidth increases the spread between the buy and sell returns with the spread difference proportionally related to the bandwidth.

The results show that profits are inconsistent across subperiods. Most of the trading rules' buy and sell profits become insignificant in subperiods. Even for the $(1, 50)$ trading rules, their buy and sell profits remain significant only in the first two subperiods (1972–1978 and 1979–1985). In addition, the magnitude of the returns decreases over the four subperiods. The trading rules with the highest returns in each subperiod are always the $(1, 50)$ rules. Our results are different from the consistent subperiod results found in Brock *et al.* (1992). We conjecture that the inconsistent results are due to the fact that the Hong Kong stock market is becoming more and more efficient over time.

Table 3 reports returns generated by the out of sample test. Since the results are very similar for different bandwidths, we only report the results for bandwidths 0 and 1. Full sample period results are shown in Panel A. Similar to the traditional test, all buy and short selling returns are statistically larger than the unconditional MDR. The out of sample tests generate 430 and 216 trading transactions for band 0 and 1%, respectively during the 35 years of the study, which average 12.29 and 6.17 trading transactions per year, respectively. It is noteworthy that the out of sample tests have consistently chosen only one single trading rule, namely $(1, 50)$, for the full period of the study.

The average daily buy return for the $(1, 50, 0)$ trading rule is 0.14% (35% annually), and is substantially and significantly higher than the benchmark MDR of 0.0648% (16.20% annually). For short selling, the average daily sell return of $(1, 50, 0)$ is -0.07% (-17.5% annually), which is also significantly different from the benchmark MDR. The buy–sell daily return of $(1, 50, 0)$ is 0.21% (52.50% annually), which is significantly greater than the daily benchmark MDR even at the 1% level. Panel B shows the results of each of the four nonoverlapping subperiods. As we did previously, we also report the results for bandwidth 0 and 1 in the table. The subperiod tests serve three purposes here. The first purpose is to test the consistency of the trading rules. The second purpose is to check which trading rule is the most useful and profitable rule in the 20 trading rules. The third and last purpose is to check whether the trading rule changes its usefulness with different testing periods and starting subperiod dates.

In Panel B, except the first and second subperiods, both buy and sell returns are insignificantly different from the benchmark unconditional MDR in the four subperiods. The magnitude of the profit also decreases over time with profit in early subperiods higher than those in the later subperiods. For example, the buy and sell profits for $(1, 50, 0)$ in the first subperiod (1972–1978) are 0.27 and -0.21%, respectively, while those of the profits in the fourth subperiods are 0.07 and -0.02%, respectively. The magnitude of the profit in the fourth subperiod is very close to the benchmark daily MDR. Therefore, profit consistency for the buy and sell strategies is not held in the subperiods. However, the buy–sell returns are significantly greater than the benchmark daily return in the first and second subperiods, the pre-1986 subperiods.

In sum, the out of sample test has helped us to identify a profitable trading strategy, the $(1, 50)$ trading rule, which gives us returns statistically

Table 3. VMA – out of sample test result[a]

Test	N(Trades)	N(Buy)	N(Sell)	N(Rules)	Most chosen rule	Buy	Sell	Buy–Sell
Panel A: Full period results (1972–2006)								
OFS 0%	430	5236	3245	1	(1, 50)	0.14% (2.36**)	−0.07% (−3.45*)	0.21% (5.05*)
OFS 1%	216	5307	3174	1	(1, 50)	0.14% (2.21**)	−0.06% (−3.32*)	0.20% (4.81*)
OFS 2%	164	5324	3154	1	(1, 50)	0.13% (1.89***)	−0.05% (−2.86*)	0.17% (4.12*)
OFS 3%	140	5242	3236	1	(1, 50)	0.12% (1.61)	−0.03% (−2.40**)	0.15% (3.49*)
					Average	0.09%	0.00%	0.09%
						0.87	−1.65***	2.17**
Panel B: Subperiod results								
(A) Subperiod 1: 1972 – 1978								
OFS 0%	65	799	770	1	(1, 50)	0.27% (2.05**)	−0.21% (−2.40**)	0.48% (3.86*)
OFS 1%	39	802	767	1	(1, 50)	0.25% (1.82***)	−0.19% (−2.18**)	0.43% (3.47*)
OFS 2%	31	824	742	1	(1, 50)	0.23% (1.68***)	−0.18% (−2.08**)	0.41% (3.26*)
OFS 3%	27	804	762	1	(1, 50)	0.22% (1.58)	−0.16% (−1.92***)	0.38% (3.03*)
(B) Subperiod 2: 1979–1985								
OFS 0%	87	1098	618	1	(1, 50)	0.17% (1.11)	−0.06% (−1.73***)	0.23% (2.47**)
OFS 1%	37	1086	630	1	(1, 50)	0.19% (1.35)	−0.09% (−2.03**)	0.28% (2.93*)
OFS 2%	35	1062	652	1	(1, 50)	0.16% (0.93)	−0.03% (−1.37)	0.19% (1.99**)
OFS 3%	31	1076	638	1	(1, 50)	0.14% (0.67)	0.00% (−1.03)	0.14% (1.47)
(C) Subperiod 3: 1986–1995								
OFS 0%	116	1712	749	1	(1, 50)	0.12% (0.74)	0.00% (−1.33)	0.13% (1.79***)
OFS 1%	66	1747	708	1	(1, 50)	0.11% (0.47)	0.03% (−0.86)	0.08% (1.16)
OFS 2%	48	1769	685	1	(1, 50)	0.10% (0.33)	0.04% (−0.59)	0.06% (0.79)
OFS 3%	38	1774	662	1	(1, 50)	0.10% (0.25)	0.06% (−0.42)	0.04% (0.58)
(D) Subperiod 4: 1996–2006								
OFS 0%	162	1567	1100	1	(1, 50)	0.07% (0.68)	−0.02% (−1.01)	0.10% (1.47)
OFS 1%	74	1606	1061	1	(1, 50)	0.08% (0.72)	−0.03% (−1.10)	0.10% (1.58)
OFS 2%	50	1602	1065	1	(1, 50)	0.08% (0.75)	−0.03% (−1.13)	0.11% (1.64)
OFS 3%	44	1503	1164	1	(1, 50)	0.07% (0.58)	−0.01% (−0.83)	0.08% (1.23)

Notes: [a]The test period is from 1972 to 2006. Rules are classified as short, long and band. Short represents the length of the short moving average and long represents the length of the long moving averages. OFS 0% represents out of sample test with a zero percentage band. Band is the percentage difference between the long and short moving averages required to generate a signal. '*N*(trade)' represents the number of trades or transactions made. '*N*(buy)' and '*N*(sell)' represent the total number of buy and sell days generated within the period. *N*(Rules) is the total number of trading rules chosen by out of sample test over the period of study. Buy and Sell are 1-day lag average buy and sell returns, respectively. Numbers below the percentage return are the corresponding *t*-value (in parenthesis) is testing the difference of the mean buy and sell returns from the unconditional mean return, and the buy–sell from zero. *, ** and *** represent significance at the 1, 5 and 10% levels respectively.

greater than the daily benchmark return and the daily buy-and-hold return.[6] However, the performance of the trading strategy does not seem to be consistent across subperiods. The strategy works better in the early pre-1986 period when the stock market was supposed to be rather inefficient. However, after 1986 when the four stock exchanges merged and the Hong Kong stock market started to grow, the profitable returns disappeared. The results seem to indicate that Hong Kong stock market was becoming more and more efficient after 1986. In addition, we also tried using different starting dates for the subperiods to perform the out of sample tests. The (1, 50) rule always emerged as the most useful and profitable trading rule no matter which starting dates (1972, 1979, 1986 or 1996) we used in the tests. In general, the (1, 50) trading rule is still the most profitable and useful trading rule among the 20 rules tested. However, it is profitable before 1986 but not after 1986. The latter finding contradicts some of the previous studies that returns are predictable in Hong Kong, which suggests that the Hong Kong stock market may be efficient in its weak form after 1986.

[6] The daily buy-and-hold strategy returns for the full and four subperiods are 0.05% (1972–2006), 0.02% (1972–1978), 0.08% (1979–1985), 0.08% (1986–1995) and 0.01% (1996–2006).

Table 4. FMA trading strategy[a]

Period	Test	*N*(Buy)	*N*(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy–sell
Panel A: Full sample								
1972–2006	(1, 50, 0)	5085	3405	0.14%	−0.05%	0.54	0.51	0.18%
				2.13**	−2.95*			4.40*
	(1, 150, 0)	5469	3163	0.11%	−0.01%	0.54	0.51	0.11%
				1.31	−1.85***			2.74*
	(1, 200, 0)	5310	3007	0.07%	0.03%	0.53	0.50	0.04%
				0.14	−0.91			0.98
	Average			0.09%	0.01%			0.08%
				0.71	−1.52			1.96**
Panel B: Four subperiods								
1972–1978	(1, 50, 0)	795	775	0.27%	−0.21%	0.53	0.56	0.49%
				2.07**	−2.40**			3.87*
	(1, 150, 0)	953	759	0.18%	−0.11%	0.53	0.55	0.29%
				1.32	−1.48			2.47**
	(1, 200, 0)	732	665	0.02%	−0.05%	0.50	0.54	0.07%
				−0.27	−0.90			0.61
1979–1985	(1, 50, 0)	1095	623	0.19%	−0.09%	0.55	0.52	0.29%
				1.37	−2.09**			3.01*
	(1, 150, 0)	1063	579	0.14%	−0.01%	0.54	0.50	0.15%
				0.68	−1.09			1.52
	(1, 200, 0)	1047	658	0.11%	0.05%	0.53	0.48	0.06%
				0.25	−0.50			0.66
1986–1995	(1, 50, 0)	1632	831	0.11%	0.04%	0.54	0.48	0.07%
				0.44	−0.69			0.98
	(1, 150, 0)	1754	683	0.08%	0.11%	0.54	0.47	−0.03%
				−0.09	0.30			−0.36
	(1, 200, 0)	1758	677	0.07%	0.13%	0.53	0.47	−0.06%
				−0.27	0.64			−0.79
1996–2006	(1, 50, 0)	1549	1165	0.05%	0.01%	0.52	0.49	0.04%
				0.29	−0.43			0.63
	(1, 150, 0)	1529	1058	0.08%	−0.02%	0.54	0.52	0.10%
				0.69	−0.95			1.42
	(1, 200, 0)	1589	986	0.07%	−0.01%	0.54	0.52	0.08%
				0.56	−0.79			1.16

Notes: [a]The test period is from 1972 to 2006. Rules are classified as short, long and band. Short represents the length of the short moving average and long represents the length of the long moving averages. Band is the percentage difference between the long and short moving averages required to generate a signal. '*N*(buy)' and '*N*(sell)' represent the total number of buy and sell days generated within the period. Numbers below the percentage return are the corresponding *t*-ratios. The *t*-value is testing the difference of the mean buy and sell returns from the 10-day unconditional mean return, and the buy–sell from zero. Buy and Sell are 1-day lag average buy and sell returns, respectively. 'Buy > 0' and 'Sell > 0' measures the probability of getting a positive return in a buy and sell day. *, ** and *** represent significance at the 1, 5 and 10% levels, respectively.

FMA strategy. The FMA trading strategy, a variation of VMA, further assumes that returns will be different for some time and it requires investors to stay in the same position after a crossing for a fixed period of time – 10 days in our study. Table 4 shows the findings of the full sample period and sub-periods. The results are similar with the findings of VMA (Table 2). The main difference is that both buy and sell return figures are slightly lower than those of VMA (Table 2). For the full sample period, only the buy and sell returns of the (1, 50) trading rules are significantly greater than the benchmark 10-day MDR. For example, the average buy and sell returns for (1, 50, 0) are 0.14% (35% annually) and −0.05% (−12.5%), respectively, which is significantly higher than the benchmark 10-day MDR of 0.0648% (16.20% annually) at the 5% level. The buy and sell returns of other trading rules are all insignificantly different from the benchmark return. Similar to the VMA, the average buy and sell returns are insignificantly different from zero (0.09 and 0.01%, respectively) while the buy–sell returns are significantly different from zero with an average of 0.08% (20% annually) for the 20 trading rules. For the 1-day lag average buy and sell returns, the values remain insignificantly at 0.09% (22.50% annually) and 0.01% (2.50% annually), which are slightly different

Table 5. FMA – out of sample test result[a]

Test	N(Trades)	N(Buy)	N(Sell)	N(Rules)	Most chosen rule	Buy	Sell	Buy–Sell
Panel A: Full period results (1972–2006)								
OFS 0%	250	5090	3391	1	(1, 50)	0.14% (2.20**)	−0.05% (−3.09*)	0.19% (4.59*)
OFS 1%	192	5214	3267	1	(1, 50)	0.13% (2.05**)	−0.05% (−3.00*)	0.18% (4.39*)
OFS 2%	154	5265	3213	1	(1, 50)	0.13% (1.92***)	−0.05% (−2.86*)	0.17% (4.15*)
OFS 3%	136	5214	3264	1	(1, 50)	0.12% (1.58)	−0.03% (−2.34**)	0.14% (3.40*)
Average						0.09%	0.00%	0.09%
						0.77	−1.56	2.01**
Panel B: Subperiod results								
(A) Subperiod 1: 1972–1978								
OFS 0%	41	795	774	1	(1, 50)	0.27% (2.08**)	−0.21% (−2.41**)	0.49% (3.89*)
OFS 1%	33	802	767	1	(1, 50)	0.26% (1.94***)	−0.20% (−2.30**)	0.46% (3.67*)
OFS 2%	29	821	745	1	(1, 50)	0.24% (1.75***)	−0.19% (−2.15**)	0.43% (3.39*)
OFS 3%	27	805	761	1	(1, 50)	0.21% (1.44)	−0.14% (−1.77***)	0.35% (2.79*)
(B) Subperiod 2: 1979–1985								
OFS 0%	39	1095	621	1	(1, 50)	0.19% (1.37)	−0.09% (−2.09**)	0.29% (3.00*)
OFS 1%	35	1088	628	1	(1, 50)	0.18% (1.22)	−0.07% (−1.86***)	0.25% (2.67*)
OFS 2%	35	1059	655	1	(1, 50)	0.15% (0.78)	−0.01% (−1.16)	0.16% (1.68***)
OFS 3%	31	1076	638	1	(1, 50)	0.14% (0.67)	0.00% (−1.03)	0.14% (1.47)
(C) Subperiod 3: 1986–1995								
OFS 0%	77	1629	832	1	(1, 50)	0.11% (0.50)	0.03% (−0.84)	0.08% (1.17)
OFS 1%	64	1682	773	1	(1, 50)	0.09% (0.09)	0.07% (−0.16)	0.02% (0.22)
OFS 2%	44	1738	716	1	(1, 50)	0.11% (0.40)	0.04% (−0.70)	0.07% (0.95)
OFS 3%	36	1755	681	1	(1, 50)	0.10% (0.32)	0.05% (−0.55)	0.05% (0.75)
(D) Subperiod 4: 1996–2006								
OFS 0%	93	1557	1153	1	(1, 50)	0.06% (0.38)	0.01% (−0.54)	0.05% (0.79)
OFS 1%	60	1576	1091	1	(1, 50)	0.08% (0.75)	−0.03% (−1.10)	0.10% (1.61)
OFS 2%	46	1580	1087	1	(1, 50)	0.08% (0.80)	−0.03% (−1.17)	0.11% (1.71***)
OFS 3%	42	1493	1174	1	(1, 50)	0.07% (0.58)	−0.01% (−0.83)	0.08% (1.23)

Notes: [a]The test period is from 1972 to 2006. Rules are classified as short, long and band. Short represents the length of the short moving average and long represents the length of the long moving averages. OFS 0% represents out of sample test with a zero percentage band. Band is the percentage difference between the long and short moving averages required to generate a signal. 'N(trade)' represents the number of trades or transactions made. 'N(buy)' and 'N(sell)' represent the total number of buy and sell days generated within the period. N(Rules) is the total number of trading rules chosen by out of sample test over the period of study. Numbers below the percentage return are the corresponding t-ratios. Buy and Sell are 1-day lag average buy and sell returns, respectively. The t-value (in parenthesis) is testing the difference of the mean buy and sell returns from the 10-day unconditional mean return, and the buy–sell from zero. *, ** and *** represent significance at the 1, 5 and 10% levels, respectively.

from the findings of Bessembinder and Chan (1995) (0.067 and –0.043%, respectively).

The result of the FMA trading rules is expected. As all signals during the immediate 9 trading days after the cross are ignored, the accuracy of FMA should be less than VMA. Even though the returns of FMA are slightly lower than those of the VMA, it seems that the information within the first 9 trading days of the signal is still valuable to investors. By making use of this information, investors, utilizing the VMA strategy, can improve their annual trading profits by a few percentage points. With the information within the 9 trading days, investors' average buy–sell returns are on average higher in the VMA (0.09%) than those of the FMA (0.08%), which further indicates that the information within the first 9 trading days is valuable to investors.

The results of subperiods are shown in Panel B of Table 4. In each of the four subperiods, the pattern of t-values and return figures for both buy and sell more or less resembles than those of the VMA except that the returns and t-values are slightly smaller. The average buy and sell returns of subperiods decrease over time with the first subperiod having the highest average returns and last subperiod having the lowest returns. This is the same as the VMA, only the (1, 50) trading rule generates significant profits in the first and second subperiods – the two pre-1986 subperiods.

Out of sample test results are presented in Table 5. With a 0% trading band, the out of sample test requires investors to transact 250 times over the 35 years of the study, which is approximately half of the VMA's. Over the full sample period, the out of sample test has again chosen only one single trading strategy, the (1, 50) rule, as the best trading rule across all 20 trading rules. The buy returns, except returns from trading strategy with 3% bandwidth, are significantly larger than the benchmark unconditional mean daily return at the 5% level. However, all sell returns are significantly different from the benchmark MDR at the 5% level. The mean return is the smallest when a 3% bandwidth is used but the difference between bands are small.

The same testing procedures are again repeated for each of the four subperiods. Except for the 3% bandwidth buy return, buy (sell) returns are positive (negative) and significantly larger than the benchmark unconditional mean daily return for the first subperiod (1972–1978). For the second subperiod (1979–1985), buy returns are all positively insignificantly different from the benchmark return. For the sell returns, only the returns from the 0 and 1% trading strategies are significantly different from the benchmark return. The rest of the sell returns are insignificant. The buy and sell returns in the next two subperiods are all insignificantly different from the benchmark return.

From the FMA out of sample tests, we find that the trading rule (1, 50) is still the most profitable trading rule for all four subperiods. But the buy returns are only significant in the first two pre-1986 subperiods, which is very similar to the result of the out of sample test in the VMA (Table 3). From the results of the tests, both the FMA traditional and out of sample tests further confirm that trading rule (1, 50), on all four bandwidths, is the most profitable trading rule among the 20 rules we study in this article. However, the (1, 50) trading rule works better before 1986. Using SMA trading rules after 1986, we cannot generate any significant profit over the daily benchmark return and the daily buy-and-hold return (refer to footnote 6), which indicates again that the Hong Kong stock market is possibly more efficient after 1986.[7]

Trading Range Break (TRB) strategy. Full sample and subperiod results generated by the TRB rule are presented in Table 6. Over the 35 years of the study, no mean buy and sell returns are statistically larger than the unconditional mean daily return at the 5% level. For the full sample (Panel A), the average daily buy and sell returns are 0.07% (17.5% annually) and 0.05% (12.5% annually), respectively. The buy–sell return is also the largest (0.10% daily or 25% annually) for the (50, 0) rule with very high *t*-value (2.19). The average buy–sell return for all 20 rules is 0.02% (5% annually). Both the (50, 0) and the average buy–sell returns are lower than the SMA (1, 50) rules' average return. The probability of having a gain on both buy and sell days is 0.53 and 0.50, respectively. All the buy, sell and buy–sell returns are insignificantly different from the benchmark return except the (50, 0) buy–sell return. It seems that the returns generated by the TRB strategy are not that impressive and are lower than both the VMA and FMA trading strategies.

For the four subperiods (Panel B), we observe similar patterns with all buy, sell and buy–sell returns insignificantly different from the benchmark return. All the returns decrease over subperiods with the early subperiods having higher returns. This pattern is the same as those in the VMA and FMA tests. In general, the profitable buy and buy–sell returns are inconsistent across subperiods and, unlike the FMA and VMA, all the profitable returns are insignificant.

The results of the out of sample test are shown in Table 7. Similar to the SMA, the out of sample test method consistently chooses the 50-day rule for all trade bandwidth during each of the 35 years of the study. For zero trading bandwidth, the out of sample test requires investors to make 103 transactions over the full sample period of the study. All average buy and sell returns are statistically insignificantly different from the unconditional MDR at the 5% level. The average buy–sell returns are positive and significantly different from the unconditional MDR and the buy-and-hold return only for the zero bandwidth strategy.

Panel B reports the result for each of the four subperiods. The buy and sell returns are all

[7] Short selling was not allowed before 1993 on the Hong Kong stock market. Another possible arbitration is through the futures market. However, the HSI futures began trading on 6 May 1986. Therefore, we conjecture that this is one of the reasons for the significant profitable findings observed in the two subperiods before 1986, as the restriction on short selling causes the significant trading profits in the first two subperiods (up to 1986), which cannot be arbitraged away, and causes reduced significant (or insignificant) profits because of the arbitrage activities in the index futures market in the third subperiod.

Table 6. TRB trading strategy[a]

Period	Test	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy–Sell
Panel A: Full sample								
1972–2006	(50, 0)	5293	3320	0.10%	0.01%	0.53	0.50	0.09%
				1.08	−1.46			2.19**
	(150, 0)	5303	2979	0.06%	0.06%	0.53	0.50	0.00%
				−0.26	−0.12			−0.08
	(200, 0)	5583	2620	0.07%	0.04%	0.53	0.51	0.03%
				0.18	−0.59			0.71
	Average			0.07%	0.05%			0.02%
				0.07	−0.33			0.33
Panel B: Four subperiods								
1972–1978	(50, 0)	946	747	0.19%	−0.13%	0.53	0.56	0.32%
				1.40	−1.63			2.62*
	(150, 0)	746	616	0.05%	−0.06%	0.50	0.55	0.11%
				0.00	−0.88			0.81
	(200, 0)	814	469	0.04%	−0.02%	0.49	0.52	0.06%
				−0.06	−0.54			0.50
1979–1985	(50, 0)	974	733	0.10%	0.07%	0.53	0.48	0.03%
				0.09	−0.23			0.29
	(150, 0)	418	637	−0.03%	0.09%	0.50	0.48	−0.12%
				−1.10	0.01			−1.01
	(200, 0)	527	527	0.02%	0.08%	0.52	0.50	−0.06%
				−0.71	−0.07			−0.55
1986–1995	(50, 0)	1784	654	0.09%	0.07%	0.53	0.47	0.02%
				0.13	−0.15			0.23
	(150, 0)	1323	709	0.00%	0.20%	0.52	0.46	−0.19%
				−1.41	1.54			−2.51**
	(200, 0)	1339	693	0.04%	0.12%	0.53	0.49	−0.08%
				−0.71	0.49			−0.99
1996−2006	(50, 0)	5293	3320	0.10%	0.01%	0.53	0.50	0.09%
				0.39	−0.45			0.73
	(150, 0)	5303	2979	0.06%	0.06%	0.53	0.50	0.00%
				0.23	−0.38			0.54
	(200, 0)	5583	2620	0.07%	0.04%	0.53	0.51	0.03%
				0.53	−0.80			1.16

Notes: [a]The test period is from 1972 to 2006. Rules are classified as short, long and band. Short represents the length of the short moving average and long represents the length of the long moving averages. Band is the percentage difference between the long and short moving averages required to generate a signal. '*N*(buy)' and '*N*(sell)' represent the total number of buy and sell days generated within the period. Numbers below the percentage return are the corresponding *t*-ratios. The *t*-value is testing the difference of the mean buy and sell returns from the unconditional mean return, and the buy–sell from zero. Buy and Sell are 1-day lag average buy and sell returns, respectively. 'Buy > 0' and 'Sell > 0' measures the probability of getting a positive return in a buy and sell day. * and ** represent significance at the 1 and 5% levels, respectively.

insignificantly different from the unconditional MDR except the first subperiod while the buy–sell returns are insignificant for bandwidth 3% only. The out of sample results suggest that the TRB rule provides lower profitable returns than those of the VMA and FMA rules for the full sample and the four subperiods. For example, the average buy and sell returns for the TRB full period sample (bandwidth 0 and 1) are 0.10 and 0.09%, respectively while the corresponding buy–sell returns for the VMA rules are 0.14%, 0.14%, and for the FMS are 0.14 and 0.13%, respectively.

From the traditional and out of sample tests of the VMA, FMA and TRB rules, we can observe the following results. First, the (1, 50) rule is the most profitable SMA trading rule that we can use in Hong Kong stock market among the 20 SMA rules we tested. The results further indicate that the VMA rule perform better than the FMA rule by including the information of the first 9 days into investors' decision. Second, it suggests that the (1, 50) SMA rule is capable of capturing useful information for investors to predict the market movement of the Hong Kong stock market before 1986, but not after 1986. Whether this indicates that the Hong Kong stock market is weak-form inefficient before 1986 and efficient after 1986, we cannot conclude from the tests in this article and further

Table 7. TRB – out of sample test result[a]

Test	N(Trades)	N(Buy)	N(Sell)	N(Rules)	Most chosen rule	Buy	Sell	Buy–Sell
Panel A: Full period results (1972–2006)								
OFS 0%	103	5284	3320	1	(1, 50)	0.10% (1.07)	0.01% (−1.47)	0.09% (2.19**)
OFS 1%	81	5276	3306	1	(1, 50)	0.09% (0.78)	0.02% (−1.07)	0.07% (1.60)
OFS 2%	55	4060	4475	1	(1, 50)	0.08% (0.37)	0.05% (−0.46)	0.03% (0.72)
OFS 3%	26	1883	6550	1	(1, 50)	0.08% (0.22)	0.06% (−0.28)	0.02% (0.39)
					Average	0.07%	0.05%	0.02%
						0.09	−0.39	0.38
Panel B: Subperiod results								
(A) Subperiod 1: 1972–1978								
OFS 0%	18	946	746	1	(1, 50)	0.19% (1.40)	−0.13% (−1.64)	0.32% (2.64*)
OFS 1%	14	882	788	1	(1, 50)	0.20% (1.40)	−0.11% (−1.51)	0.31% (2.52**)
OFS 2%	10	602	1021	1	(1, 50)	0.21% (1.35)	−0.06% (−1.11)	0.27% (2.11**)
OFS 3%	8	403	1118	1	(1, 50)	0.15% (0.71)	−0.02% (−0.70)	0.17% (1.16)
(B) Subperiod 2: 1979–1985								
OFS 0%	23	974	731	1	(1, 50)	0.10% (0.09)	0.07% (−0.23)	0.03% (0.28)
OFS 1%	19	992	711	1	(1, 50)	0.11% (0.18)	0.06% (−0.39)	0.05% (0.50)
OFS 2%	15	1067	636	1	(1, 50)	0.08% (−0.18)	0.10% (0.09)	−0.02% (−0.23)
OFS 3%	10	546	1042	1	(1, 50)	−0.03% (−1.25)	0.15% (0.77)	−0.18% (−1.76***)
(C) Subperiod 3: 1986–1995								
OFS 0%	30	1776	660	1	(1, 50)	0.09% (0.12)	0.07% (−0.18)	0.02% (0.25)
OFS 1%	22	1770	663	1	(1, 50)	0.08% (−0.11)	0.11% (0.29)	−0.03% (−0.36)
OFS 2%	14	1215	1213	1	(1, 50)	0.07% (−0.34)	0.11% (0.45)	−0.04% (−0.68)
OFS 3%	6	557	1727	1	(1, 50)	0.06% (−0.32)	0.09% (0.03)	−0.03% (−0.33)
(D) Subperiod 4: 1996–2006								
OFS 0%	32	1407	1164	1	(1, 50)	0.06% (0.36)	0.01% (−0.43)	0.04% (0.68)
OFS 1%	26	1293	1123	1	(1, 50)	0.03% (−0.23)	0.04% (−0.00)	−0.01% (−0.19)
OFS 2%	16	821	1584	1	(1, 50)	0.01% (−0.40)	0.05% (0.12)	−0.03% (−0.47)
OFS 3%	2	377	1656	1	(1, 50)	0.16% (1.36)	0.03% (−0.16)	0.13% (1.43)

Notes: [a]The test period is from 1972 to 2006. Rules are classified as short, long and band. Short represents the length of the short moving average and long represents the length of the long moving averages. OFS 0% represents out of sample test with a zero percentage band. Band is the percentage difference between the long and short moving averages required to generate a signal. '*N*(trade)' represents the number of trades or transactions made. '*N*(buy)' and '*N*(sell)' represent the total number of buy and sell days generated within the period. *N*(Rules) is the total number of trading rules chosen by out of sample test over the period of study. Buy and Sell are 1−day lag average buy and sell returns, respectively. Numbers below the percentage return are the corresponding *t*-value (in parenthesis) testing the difference of the mean buy and sell returns from the unconditional mean return, and the buy–sell from zero. *, ** and *** represent significance at the 1, 5 and 10% levels, respectively.

research is needed. Third, the (1, 50) SMA rules (includes both VMA and FMA rules) provide higher profits than the TRB rules. The two rules perform much better than the TRB rules, ranging up to 50%. Our results show that the (1, 50) SMA rule is the best rule among the trading rules we evaluated in this study. The only deficiency is that the rule is inconsistent across subperiods and becomes unprofitable after 1986.

Transaction costs

In this section, we also consider the impact of transaction costs on the trading rules. The round-trip transaction costs of buying stocks range from 1.17% (29 October 1987 to 1 April 1991) to 0.74% (after 7 April 2000) within our test period (*Source*: various issues of Hong Kong Stock Exchange Fact Book). The average round-trip transaction cost is, therefore, approximately 1%[8]

[8] To make computation easier, we round up the average round-trip transaction cost from 0.955 to 1% and the one-way transaction cost to 0.5%. Our transaction cost is less than those of Bessembinder and Chan (1995) by 0.57% (their breakeven transaction cost is 1.57%). We do not think it will seriously affect our test results. Their study basically covers the first two subperiods of our tests. The profits in these two subperiods are much higher than the extra 0.57%.

Table 8. Net return of out of sample test[a]

Test	N(Trades)	N(Buy)	N(Sell)	N(Rules)	Most chosen rule	Buy	Sell	Buy–Sell
VMA: Full period result (1972–2006)								
OFS 0%	430	5236	3245	1	(1, 50)	0.10%	0.00%	0.10%
						1.11	−1.73***	2.47**
OFS 1%	216	5307	3174	1	(1, 50)	0.12%	−0.03%	0.15%
						1.59	−2.44**	3.51*
OFS 2%	164	5324	3154	1	(1, 50)	0.11%	−0.02%	0.13%
						1.41	−2.19**	3.13*
OFS 3%	140	5242	3236	1	(1, 50)	0.10%	−0.01%	0.11%
						1.20	−1.84***	2.65*
FMA: Full period result 1972–2006								
OFS 0%	250	5090	3391	1	(1, 50)	0.11%	−0.02%	0.13%
						1.46	−2.11**	3.11*
OFS 1%	192	5214	3267	1	(1, 50)	0.11%	−0.02%	0.13%
						1.49	−2.24**	3.24*
OFS 2%	154	5265	3213	1	(1, 50)	0.11%	−0.02%	0.13%
						1.48	−2.24**	3.23*
OFS 3%	136	5214	3264	1	(1, 50)	0.10%	0.00%	0.11%
						1.18	1.80***	2.59*
TRB: Full period result 1972–2006								
OFS 0%	103	5284	3320	1	(1, 50)	0.09%	0.02%	0.07%
						0.77	−1.06	1.58
OFS 1%	81	5276	3306	1	(1, 50)	0.08%	0.04%	0.05%
						0.54	−0.75	1.12
OFS 2%	55	4060	4475	1	(1, 50)	0.07%	0.06%	0.02%
						0.18	−0.28	0.40
OFS 3%	26	1883	6550	1	(1, 50)	0.07%	0.06%	0.01%
						0.08	−0.22	0.21

Notes: [a]The test period is from 1972 to 2006. Rules are classified as short, long and band. Short represents the length of the short moving average and long represents the length of the long moving averages. OFS 0% represents out of sample test with a zero percentage band. Band is the percentage difference between the long and short moving averages required to generate a signal. 'N(trade)' represents the number of trades or transactions made. 'N(buy)' and 'N(sell)' represent the total number of buy and sell days generated within the period. N(Rules) is the total number of trading rules chosen by out of sample test over the period of study. Buy and Sell are 1-day lag average buy and sell returns, respectively. Numbers below the percentage return are the corresponding t-value testing the difference of the mean buy and sell returns from the unconditional mean return, and the buy–sell from zero. All profits are net of transaction costs (one-way cost = 0.5% and round trip cost = 1%). *, ** and *** represent significance at the 1, 5 and 10% levels, respectively.

and we take this average transaction cost as the transaction cost in this study.

The impact of the transaction costs on trading profits is quite insignificant.[9] The net buy, sell and buy–sell net returns for the full sample period of the three out of sample tests are reported in Table 8. The net returns are, in general, still substantial for some trading rules even after taking transaction costs into consideration. For example, the average buy, sell and buy–sell returns decrease by approximately 0.04, 0.03 and 0.01%, respectively for the VMA, FMA and TRB out of sample test 0% out of sample trading rule (Tables 3 and 8). The sell returns remain significant for out of sample test 0 to 3% for VMA and FMA while the buy returns become insignificant. However, the buy–sell returns remain significant throughout the VMA and FMA out of sample tests. Thus, in general, the effect of transaction costs on VMA, FMA and TRB rules are insignificant.

Efficiency of the Hong Kong stock market. The observation that trading strategies generate high abnormal average returns in the early pre-1986 subperiods seems to suggest that the Hong Kong stock market is inefficient before 1986. This conclusion is a bit premature and, therefore, we further explore if the high positive abnormal returns is due to

[9] The per-day transaction cost is calculated by multiplying the one-way (for buy or sell) transaction cost with the number of trades [N(Trades)] and dividing it by the number of buy [N(Buy)] or sell [N(Sell)].

the positive autocorrelation in the Hong Kong stock market. However, the small positive autocorrelation we found does not explain the high buy and sell average returns. Part of the reason that the autocorrelation is small is due to the nature of the HSI. Since constitute stocks on the HSI are all actively traded stocks, there is no 'thin trading' or 'nonsynchronous' problem in the index. The nature of the HSI would reduce the autocorrelation in the index. We do not see any substantial change in volatility between buy and sell signals. The SDs within the period on both signals remains almost the same.

Even though the high returns in our test are unlikely due to autocorrelation in stock prices, there is still another possible explanation – the transaction costs. In our case, the average returns after transaction costs are still high. The trading costs in Hong Kong, which are approximately 1% per round trip, will not affect the average returns very much. In fact, the transaction costs only reduce the average returns by 0.04% (daily) on both VMA and FMA rules. So, the transaction costs can only explain a small fraction of the high average returns.

Finally, we find that the high abnormal average returns disappear in the last two post-1986 subperiods. We conjecture that the disappearance of the high abnormal average returns in the latter subperiods is due to the consequence of stock market integration, which eventually leads to a more efficient dissemination of information. The stock market is thus becoming more and more efficient after 1986.

V. Conclusions

In this article, we investigate two simple but very popular trading rules, SMA and TRB by looking at a series of data from the HSI over 35 years, from 1972 to 2006. We apply out of sample tests to test the validity of the profitability of the trading rules. The out of sample test, which is not affected by the data-snooping biases problem, is used to check the usefulness of the traditional test.

In general, our results show that there is one trading rule, the (1, 50) rule, that outperforms the market (HSI) over the 35 years of the testing period and in the pre-1986 subperiods of our study. The out of sample average buy and sell returns for zero bandwidth on VMA strategy are 0.14 and −0.07% (35 and −17.5% annually), respectively before transaction costs. The buy (sell) returns are significantly higher (lower) than the unconditional mean daily return of 16.20% per year. The 10-day FMA strategy produces a lower average return but still the way higher than the benchmark. The average bandwidth zero buy and sell FMA out of sample test returns are 0.14 and −0.05 (35% and −12.5% annually), respectively and are statistically different (higher or lower) than the benchmark return. These returns are also higher than the returns found in the US (Brock *et al.*, 1992) and Hong Kong (Bessembinder and Chan, 1995) markets. In addition, the VMA (1, 50) rule performs better than the FMA (1, 50) rule because it includes the information of the first 9 days into investors' decisions. With the flexibility of buy or sell within the first 9 days, the VMA (1, 50) rule can generate 2.5 to 5% (annual) more profit than the FMA rule before transaction costs. However, the returns of the TRB rules are all small and insignificant.

We provide two robustness tests for the observation that trading strategies generate high abnormal average returns in the early two pre-1986 subperiods. First, the autocorrelation in the market can partially explain the high trading returns, but the magnitude is so small that it can only explain a small fraction of it. Second, transaction costs can reduce the high trading returns but, again, the reduction is very small. Finally, we find that the high abnormal average returns disappear in the post-1986 sub-periods. We conjecture that it is mainly due to the consequence of stock market integration, which eventually leads to a more efficient dissemination of information, thus causing the stock market to become more and more efficient after 1986.

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References

Alexander, S. S. (1961) Price movements in speculative markets: trends or random walks, *Industrial Management Review*, **2**, 7–26.

Alexander, S. S. (1964) Price movements in speculative markets: trends or random walks, in *The Random Character of Stock Market Prices,* Vol. 2 (Ed.) P. Cootner, MIT Press, Cambridge, MA, pp. 338–72.

Allen, H. and Taylor, M. P. (1990) Charts, noise and fundamentals in the foreign exchange market, *Economic Journal*, **100**, 49–59.

Ariel, R. (1987) A monthly effect in stock returns, *Journal of Financial Economics*, **18**, 161–74.

Bailey, W., Stulz, R. and Yen, S. (1990) Properties of daily stock returns from the Pacific Basin Stock Markets: evidence and implications, in *Pacific-Basin Capital Markets Research*, Vol. 1 (Eds) S. Rhee and R. Chang, North-Holland, Amsterdam, pp. 155–71.

Bessembinder, H. and Chan, K. (1995) The profitability of technical trading rules in Asian stock markets, *Pacific-Basin Finance Journal*, **3**, 257–84.

Bessembinder, H. and Chan, K. (1998) Market efficiency and the returns to technical analysis, *Financial Management*, **27**, 5–17.

Blume, L., Easley, D. and O'Hara, M. (1994) Market statistics and technical analysis: the role of volume, *Journal of Finance*, **49**, 155–81.

Brock, W., Lakonishok, J. and LeBaron, B. (1992) Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance*, **47**, 1731–64.

Cheung, Y. L. and Ho, Y. K. (1991) The intertemporal stability of the relationships between the Asian emerging equity markets and the developed equity markets, *Journal of Business Finance and Accounting*, **18**, 235–53.

Chopra, N., Lakonishok, J. and Ritter, J. R. (1992) Performance measurement methodology and the question of whether stocks overreact, *Journal of Financial Economics*, **31**, 235–68.

Conrad, J. and Kaul, G. (1989) Mean reversion in short-horizon expected returns, *The Review of Financial Studies*, **2**, 225–40.

Coutts, J. A. and Cheung, K. C. (2000) Trading rules and stock returns: some preliminary short run evidence from the Hang Seng 1985–1997, *Applied Financial Economics*, **10**, 579–86.

De Bondt, W. F. M. and Thaler, R. H. (1985) Does the stock market overreact?, *Journal of Finance*, **40**, 793–805.

De Bondt, W. F. M. and Thaler, R. H. (1987) Further evidence on investor overreaction and stock market seasonality, *Journal of Finance*, **42**, 557–81.

Dickson, J. P. and Moragu, K. (1994) Market efficiency in developing countries: a case study of Nairobi Stock Exchange, *Journal of Business Finance and Accounting*, **21**, 133–50.

Draper, P. and Paudyal, K. (1997) Microstructure and seasonality in the UK equity market, *Journal of Business Finance and Accounting*, **24**, 1177–204.

Fama, E. F. (1970) Efficient capital markets: a review of theory and empirical work, *Journal of Finance*, **25**, 383–423.

Fama, E. F. and Blume, M. (1966) Filter rules and stock market trading profits, *Journal of Business*, **39**, 226–41.

Fama, E. F. and French, K. R. (1988) Permanent and temporary components of stock price, *Journal of Political Economy*, **96**, 246–73.

French, K. R. (1980) Stock returns and the weekend effect, *Journal of Financial Economics*, **13**, 55–70.

Frennberg, P. and Hansson, B. (1993) Testing the random walk hypothesis on Swedish stock prices: 1919–1990, *Journal of Banking and Finance*, **17**, 175–91.

Gultekin, M. N. and Gultekin, N. B. (1983) Stock market seasonality: international evidence, *Journal of Financial Economics*, **12**, 469–82.

Ho, Y. K. (1990) Stock return seasonalities in Asia Pacific markets, *Journal of International Financial Management and Accounting*, **2**, 47–77.

Ho, Y. K. and Cheung, Y. L. (1994) Seasonal pattern in volatility in Asian stock markets, *Applied Financial Economics*, **4**, 61–7.

Hudson, R., Dempsey, M. and Keasey, K. (1996) A note on the weak-form efficiency of capital markets: the application of simple technical trading rules to UK stock prices – 1935 to 1994, *Journal of Banking and Finance*, **20**, 1121–32.

Isakov, D. and Hollistein, M. (1998) Application of simple technical trading rules to Swiss stock prices: is it profitable?, Working Paper No. 76, HEC, University of Geneva, Geneva.

Jaffe, J. and Westerfield, R. (1985) Pattern in the Japanese common stock returns: day of the week and turn of the year effects, *Journal of Financial and Quantitative Analysis*, **20**, 261–72.

Jappelli, T. and Pagano, M. (2008) Financial market integration under EMU, European Economy Economic Papers No. 312.

Jegadeesh, N. (1990) Evidence of predictable behavior of securities returns, *Journal of Finance*, **45**, 881–98.

Kato, K. and Schallheim, J. S. (1985) Seasonal and size anomalies in the Japanese Stock Market, *Journal of Financial and Quantitative Analysis*, **20**, 243–60.

Kavussanos, M. G. and Dockery, E. (2001) A multivariate test for stock market efficiency: the case of ASE, *Applied Financial Economics*, **11**, 573–79.

Keim, D. and Stambaugh, R. (1984) A further investigation of the weekend effect in stock returns, *Journal of Finance*, **39**, 819–34.

Koutmos, G., Negakis, C. and Theodossiou, P. (1993) Stochastic behaviour of the Athens Stock Exchange, *Applied Financial Economics*, **3**, 119–26.

Lakonishok, J. and Smidt, S. (1988) Are seasonal anomalies real? A ninety-year perspective, *Review of Financial Studies*, **1**, 403–25.

Lee, I., Pettit, R. R. and Swankoski, M. V. (1990) Daily return relationships among Asian stock market, *Journal of Business Finance and Accounting*, **17**, 265–84.

Lehmann, B. N. (1990) Fads, martingales, and market efficiency, *Quarterly Journal of Economics*, **105**, 1–28.

Levich, R. and Thomas, L. (1993) The significance of technical trading rule profits in the foreign exchange market: a bootstrap approach, *Journal of International Money and Finance*, **12**, 451–74.

Lewis, K. (1999) Trying to explain home bias in equity and consumption, *Journal of Economic Literature*, **37**, 571–608.

Lo, A. W. and MacKinlay, C. A. (1988) Stock market prices do not follow random walk: evidence from a simple specification test, *Review of Financial Studies*, **1**, 41–66.

Lo, A. W. and MacKinlay, C. A. (1990) Data-snooping biases in tests of financial asset pricing models, *Review of Financial Studies*, **3**, 431–68.

Lo, A. W., Mamaysky, H. and Wang, J. (2000) Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation, *Journal of Finance*, **55**, 1705–65.

McGuinness, P. M. (2005) A re-examination of holiday effect in stock returns: the case of Hong Kong, *Applied Financial Economics*, **15**, 1107–23.

Menkhoff, L. and Taylor, M. P. (2007) The obstinate passion of foreign exchange professionals: technical analysis, *Journal of Economic Literature*, **45**, 936–72.

Mills, T. C. (1997) Technical analysis and the London Stock Exchange: testing trading rules using the FT30, *International Journal of Finance and Economics*, **2**, 319–31.

Mills, T. C. and Coutts, J. A. (1995) Calender effects in the London Stock Exchange FTSE indices, *European Journal of Finance*, **1**, 79–93.

Neftci, S. N. (1991) Naïve trading rules in financial markets and Wiener–Kolmogorov prediction theory: a study of technical analysis, *Journal of Business*, **64**, 549–71.

Padilla, J. and Pagano, M. (2006) Are there gains from stock exchange integration? The Euronext evidence, Working Paper, LECG.

Pan, M., Chiou, J., Hocking, R. and Rim, H. (1991) An examination of mean-reverting behavior of stock prices in Pacific-Basin stock markets, in *Pacific-Basin Capital Markets Research*, Vol. 2 (Eds) S. Rhee and R. Ghang, North-Holland, Amsterdam, pp. 333–43.

Poterba, J. M. and Summers, L. H. (1988) Mean reversion in stock prices: evidence and implications, *Journal of Financial Economics*, **22**, 27–59.

Ratner, M. and Leal, R. P. C. (1999) Tests of technical trading strategies in the emerging equity markets of Latin America and Asia, *Journal of Banking and Finance*, **23**, 1887–905.

Reinganum, M. R. and Shapiro, A. C. (1987) Taxes and stock return seasonality: evidence from the London Stock Exchange, *Journal of Business*, **60**, 281–95.

Ritter, J. R. and Chopra, N. (1989) Portfolio balancing and the turn-of-the-year effect, *Journal of Finance*, **44**, 149–66.

Rozeff, M. and Kinney, W. (1976) Capital market seasonality: the case of stock returns, *Journal of Financial Economics*, **3**, 379–402.

Spyrou, S. I. (1998) Random walks in the Greek Stock Exchange: is the Greek capital market informationally efficient?, *Synthesis: Review of Modern Greek Studies*, **2**, 33–41.

Stulz, R. (1999) Globalization of equity markets and the cost of capital, *Journal of Applied Corporate Finance*, **12**, 8–25.

Sweeney, R. J. (1988) Some new filter rule test: methods and results, *The Journal of Financial and Quantitative Analysis*, **23**, 285–300.

Taylor, M. P. and Allen, H. (1992) The use of technical analysis in the foreign exchange market, *Journal of International Money and Finance*, **11**, 304–14.

Tesar, L. L. and Werner, I. M. (1995) Home bias and high turnover, *The Journal of International Money and Finance*, **14**, 467–92.

Wong, K. A., Hui, T. K. and Chan, C. Y. (1992) Day-of-the-week effects: evidence from developing stock markets, *Applied Financial Economics*, **2**, 49–56.

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