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# PROFITEERING FROM THE DOT-COM BUBBLE, SUBPRIME CRISIS AND ASIAN FINANCIAL CRISIS

*By* MICHAEL MCALEER,[†] JOHN SUEN[‡] and WING KEUNG WONG[§]

[†]National Tsing Hua University and Erasmus University Rotterdam [‡]Chinese University of Hong Kong [§]Hong Kong Baptist University

The paper explores the characteristics associated with the formation of bubbles that occurred in the Hong Kong stock market in 1997 and 2007, as well as the 2000 dot-com bubble of Nasdaq. It examines the profitability of technical analysis (*TA*) strategies generating buy and sell signals, with and without our proposed trading rules. The empirical results show that, by applying long and short strategies during the bubble formation and a short strategy after the bubble burst, it not only produces returns that are significantly greater than buy-and-hold strategies, but also produces greater wealth compared with *TA* strategies without trading rules. We conclude that these bubble detection signals help investors generate greater wealth from applying appropriate long and short moving average (*MA*) strategies.
JEL Classification Numbers: G1, C0.

## 1. Introduction

The past two decades have witnessed three huge bubbles and crashes with deep and long bear markets: the uncontrolled exuberance during the 1990s followed by the Asian financial crisis, the dot-com bubble at the turn of the Century, and the bubble in the run up to the 2007 peak of over 30,000, followed by the crashes and bust after the bursting of the US housing bubble. Many institutional investors suffered losses, in spite of well-established tests to detect bubbles in the stock market; namely, excess volatility tests, cointegration tests, duration dependence tests and the intrinsic bubbles model.

If such well-established tests for the existence of bubbles are available, why do such bubbles occur? Why do most investors fail to avoid the bursting of bubbles by simply leaving the market early when signals, as suggested by these quantitative tests, purportedly detect the existence of bubbles. One possible explanation may be that, even though investors may be fooled into buying an overpriced asset, they believe that the market is populated by greater fools who are willing to buy at an even higher price, the so-called “greater fool” theory. Mokhtar *et al.* (2006) suggest that such speculators know that stock prices have exceeded their fundamental value, but continue to trade while thinking that the bubble will continue. Another possible explanation is that, in practice, these bubble detection techniques are too difficult and are not available to the average investors, who have no tools to detect the stock bubbles. Consequently, such investors are not able to leave early when these signals occur to avoid market crashes and bear markets, thereafter suffering huge losses.

In this paper, we develop simple bubble detection signals that can be used by investors and regulators. We do so by analysing the 1997 stock bubble of the Hang Seng Index (HSI), the 2000 dot-com bubble and the 2007 stock bubble of the HSI. In sum, we identify four properties associated with the creation and bursting of bubbles, which serve as selling signals for investors to leave the market early before the horrendous bursting of bubbles. The four properties are as follows: (i) the run-up of abnormally high returns in the formation of the bubble; (ii) the increase in stock prices by more than 10% above the one standard deviation trend line; (iii) an increase in the volatility of stock returns; and (iv) the decline in stock prices below the one standard deviation trend line.

After identifying these four signals, we suggest a trading rule to profit from the bursting of a bubble. We assess the performance of different buy/sell rules, namely technical analysis tools from the moving average (*MA*) family, including simple *MA* rules, dual *MA* rules and exponential *MA* rules, for the three bubbles to examine which strategies can help investors profit even during bubble formation and bursting. Our findings show that *MA* perform significantly better than the buy-and-hold (*BH*) strategy, even with transaction costs. In particular, we find that the *MA*20 rule is able to generate the greatest wealth for investors.

The remainder of this paper is as follows. Section 2 provides a brief review of the literature on speculative bubbles and technical analysis. Section 3 examines the four properties associated with the build up and bursting of a bubble, with empirical results from the 1997, dot-com and 2007 bubbles. The methodology in constructing the figures will be discussed. Then we suggest a trading rule to profit from the bursting of bubbles. In Section 4, different buy/sell strategies, including *MA*(5), *MA*(10), *MA*(20), *MA*(30), *MA*(50), *DMA*(5,20), *DMA*(5,30), *EMA*(5), *EMA*(10) and *EMA*(20), are examined. We recommend trading strategies for investors to avoid similar crashes and to capture investment opportunities.

## 2. Literature review

Technical analysis (*TA*) has a long history of identifying and moving with the trend. It goes back to the 1700s, when Japanese rice traders traded on the Dojima Rice Exchange. *TA* was used widely after the 1800s, with Charles Dow laying the foundation for modern technical analysis. Later it evolved into Chartism in the early 20th century, with mechanical trading rules to generate buy/sell signals. The advent of computers enabled analysts to combine fundamental economic data with price and volume data to produce new indicators.

Technical analysis is applicable to stocks, indices, commodities, futures or any tradable instrument where prices are influenced by supply and demand. *TA* is used to analyse historical data on prices to determine future prices on the basis of trends. There are two groups of *TA*; namely, trend-following indicators and counter-trend indicators. Wong *et al.* (2003) find that most of the counter-trend indicators do not perform well in signalling. Since the seminal work of Friedman (1953) and Fama (1970), *TA* as a forecasting tool has been controversial. Some literature has found that *TA* is not useful and cannot beat buy-and-hold strategies if transaction costs are incorporated. This is probably due to the fact that there are periods when prices do not trend and fluctuate randomly (Schwager, 1995). The goal of Chartism is to identify periods of non-random major trends.

Early empirical research by Roberts (1959) and Brealey (1969) presents evidence supporting the weak form of market efficiency. Alexander (1961, 1964), who was the first to confirm the profitability of technical trading on individual US stocks, finds that profitability disappears when trading costs are introduced. Fama and Blume (1966), Jensen and Benington (1970), Fama (1970) and Fong and Yong (2005) observe some merit in *TA*. Fama and Blume (1966) even find that returns could be negative under transaction costs. Their work is consistent with the efficient market hypothesis, which states that the current price reflects all available information, including the past history of prices and trading volume, so that one cannot expect abnormal returns (Fama, 1970). Sweeney (1988) shows that filter rules similar to that of Fama and Blume (1966) can produce profits depending on the level of transaction costs.

Many researchers (e.g. Fama, 1965; Neftci, 1991) have concluded that *TA* is not able to predict future movements in the stock market, and that a simple buy-and-hold strategy outperforms trading rules. Isakov and Hollistein (1999) report that transaction costs eliminate technical trading profits in the Swiss stock market. They suggest conditions where large investors may profit from *MA* trading rules. However, Frankel and Froot (1990) find that there was a shift from fundamentals to *TA* in the 1980s, and that market practitioners rely on *TA* in forecasting the market. Moreover, the prevalence of real time information services that provide detailed, comprehensive and up-to-date technical analysis information, such as Reuters and Telerate, suggests that *TA* is used widely.

Mills (1997) analyses the trading rules using data from the London Stock Exchange FT30 index for the period 1935–1994, and finds that the rules actually work for the most of the sample period, at least up to the 1980s. However, these empirical findings are also contradictory, as after the 1980s the buy-and-hold strategy dominates the trading rule strategy. Chong and Ng (2008) reexamine the issue by using the same data set as Mills, but divide the data into three samples and review the RSI and MACD trading rules.[1] They conclude that the RSI and MACD trading rules are able to outperform the buy-and-hold strategy, and find that this conclusion is robust to their choice of the sample period. The returns for the trading rules are statistically significant at the 5% level. Other research concludes that *TA* contains significant forecasting power, and that analysts can identify a trend that can be exploited during the sluggish adjustment of stock price to fundamental supply and demand phenomena.

Wong *et al.* (2003) conclude that *TA* can be useful, and calculate test statistics which suggest that both *MA* and *RSI* indicators pass the tests in generating significant positive returns. Ratner and Leal (1999) estimate the efficacy of using technical trading rules (10 variable length moving averages) in emerging markets of Latin America and Asia. The results demonstrate that, on average, superior profits after estimated trading costs can be achieved by technical trading rules over a simple buy-and-hold strategy only in certain countries, specifically Mexico, Taiwan and Thailand. The profitability of technical trading rules in emerging markets may be associated with the persistence of returns, or autocorrelation, in these markets. Harvey (1995a) finds that the autocorrelation in emerging markets is much higher than in developed markets. Harvey (1995b) contends that emerging market returns seem to be predictable when using international and local risk factors.

Balvers *et al.* (1990) find that stock returns can be predicted using national aggregate output. Campbell (1987), Campbell and Shiller (1988a,b), Fama and French (1989) and Breen *et al.* (1990) find that stock returns can be predicted to a large degree by the price–earnings ratio, dividend yields, business conditions and economic variables. Lo *et al.* (2000) find that US share prices over the period 1962–1996 are unusually recurrent. Although they do not show that the patterns are predictable enough to make sufficient profits to justify the risk, the authors conclude that this is possible. Wong *et al.* (2005) conclude that in the Shanghai, Hong Kong and Taiwan stock exchanges, *TA* outperforms a buy-and-hold strategy, and that the cumulative wealth obtained also surpasses that of the buy-and-hold strategy under transaction costs. The conclusion is that the Greater China stock markets, in general, are not efficient.

Allen and Taylor (1990) and Neftci (1991) find that simple *TA* has significant forecasting power. Brock *et al.* (1992) demonstrate that a relatively simple set of technical trading rules possesses significant forecasting power for changes in the Dow Jones Industrial Average over a long sample period. However, Ready (1997) finds that, apart from the earlier sub-period 1970–1974, *MA* generally underperforms the buy-and-hold strategy. Bessembinder and Chan

[1] RSI is a "relative strength index". It is a technical momentum indicator that compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold. MACD is "moving average convergence divergence". It is a trend-following momentum indicator that shows the relationship between two moving averages of prices. Kindly refer to Chan *et al.* (2014) for more information.

(1998) find that the Brock *et al.* (1992) trading rules can be profitable in some Asian countries when trading costs are considered. Hudson *et al.* (1996) find that the Brock *et al.* (1992) trading rules have some ability to predict the FT30 series of returns, but that no significant gains are found after factoring in trading costs.

Kung and Wong (2009a) conduct an analysis using two popular trading rules, namely *MA* and *TRB*, to assess whether or not the gradual liberalization of Taiwan's securities markets has improved the efficiency of its stock market. The results show that the two rules have considerable predictive power for 1983–1990; become less predictive for 1991–1997, and cannot predict the market for 1998–2005. These results indicate that the efficiency of the Taiwan stock market has been greatly enhanced by the liberalization measures implemented over the past 20 years.

In spite of the multitude of published papers on *TA*, only a few have addressed bubbles and downturns. Wong *et al.* (2001) examine whether buy/sell signals generated from the price–earnings ratio and bond yield could help investors avoid market crashes and beat the stock market. They conclude that the trading signals from the indicator can enable investors to escape from most of the crashes and catch most of the bull runs, thereby generating significant profits. Other attempts include Fisher and Statman (2003), who find that consumer confidence is able to predict some stock returns when predicting Nasdaq and small cap stock returns. They find a negative and statistically significant relationship between the level of the expectations component of the Conference Board confidence in one month in Nasdaq and small cap stocks in the following month. However, they do not find the same relationship to be statistically significant when considering the S&P 500 index.

In addition, Lam *et al.* (2007) examine whether a day's surge or plummet in stock price can serve as a market entry or exit signal. They find that the trading rules perform well in the Asian indices but not in those of Europe and the USA. In the aftermath of the Asian financial crisis, a series of reform and liberalization measures have been implemented in Singapore to upgrade its financial markets. Kung and Wong (2009b) investigate whether these measures have led to less profitability for those investors who employ technical rules for trading stocks. They find that the three trading rules consistently generate higher annual returns for 1988–1996 than those for 1999–2007. Furthermore, they generally perform better than the buy-and-hold strategy for 1988–1996, but perform no better than the buy-and-hold strategy for 1999–2007. These findings suggest that the efficiency of the Singapore stock market has been considerably enhanced by the measures implemented after the crisis.

Wong and McAleer (2009) examine the presidential election cycle and find that stock prices fall during the first half of a presidency, reach a trough in the second year, rise during the second half of a presidency, and reach a peak in the third or fourth year. They also find that the Republican Party may have greater cause to engage in active policy manipulation to win re-election than their Democratic counterparts.

In this paper we use simple *TA* tools, including the moving regression lines, and indicators such as stock returns and volatility to signal the formation and bursting of financial bubbles in HSI during 1997 and 2007 and Nasdaq during 2000. The paper also examines different technical trading rules to see which strategy is able to generate the greatest wealth for investors.

## 3. Four properties common to the 1997, dot-com and 2007 bubbles

### 3.1 Property 1: Accumulation of abnormally high returns

We first consider the 1997 bubble. Table 1 shows that during the 2-year period before the 4 months preceding the peak of the 1997 bubble, the ratio of the number of days with positive

TABLE 1
Stock returns before the bubble, and during the bull runs and bear markets of the bubble

| Period | % of positive returns | % of negative returns | Average daily returns (%) | Returns for the period (annualized, %) |
|---|---|---|---|---|
| 1997 bubble | | | | |
| 17 July 1995 to 29 April 1997 | 52.6 | 47.4 | 0.06 | 16.7 |
| 29 April 1997 to 7 August 1997 | 59.4 | 40.6 | 0.40 | 118.1 |
| 7 July 1995 to 13 August 1998 | 51.1 | 48.9 | −0.05 | −10.4 |
| Dot-com bubble | | | | |
| 2 January 1997 to 19 October 1999 | 56.5 | 43.5 | 0.11 | 44.4 |
| 19 October 1999 to 10 March 2000 | 68.0 | 32.0 | 0.63 | 221.3 |
| 31 August 1998 to 9 September 2002 | 53.4 | 46.6 | 0.00 | 0.3 |
| 2007 bubble | | | | |
| 13 June 2005 to 11 June 2007 | 56.7 | 42.1 | 0.08 | 24.1 |
| 11 June 2007 to 30 October 2007 | 58.4 | 37.6 | 0.43 | 133.4 |
| 10 June 2005 to 9 March 2009 | 53.0 | 45.2 | −0.02 | −6.1 |

*Note*: The table shows the percentage of days with positive and negative returns, the average daily returns and returns for the period (annualized) for the periods before and during the bubble formation.

returns to the number of days with negative returns of the HSI daily index is around 53:47. However, in the 4 months preceding the 1997 peak, the ratio increases to 59:40, a significant increase in the proportion of days with positive returns. A similar pattern is seen in the dot-com bubble, with the ratio for Nasdaq daily returns increasing from 56:44 to 68:32 for the 5 months preceding the 2000 peak. A similar increase in the ratio is seen for the 2007 bubble. The ratio increases from 56.7:42.1 for the period 10 June 2005 to 11 June 2007 to 58.4:37.6 for the 4 months preceding the 2007 peak.

As for the size of returns, for the 1997 bubble, the average daily return for HSI in the 2-year period before the 4 months preceding the 1997 peak is merely 0.06%, but it increases to 0.40% for the 4 months before the 1997 peak. The annualized return for the same 2-year period is just 16.7%, but it increases sharply to over 118.1% for the 4 months preceding the 1997 peak. For the dot-com bubble, the average daily returns for NASDAQ in the 2 years before 5 months preceding the 2000 peak is approximately 0.11%, but then it increases five times to 0.63%, with the annualized return for the corresponding period increasing from 44% to approximately 221% (see Table 1). For the 2007 bubble, the average daily return of HSI for the 2-year period preceding 4 months before the 2007 peak is merely 0.08%, which then increases significantly to 0.63% for the 4 months before the 2007 peak. The annualized return for the same 2-year period is merely 24.1%, compared with 133.4% in the 4 months preceding the 2007 peak (see Tables 2 and 3).

These results are not particularly surprising. To compensate for the possibility of a bubble bursting, investors would require higher returns during a bubble than during normal times. These two facts constitute the first property of bubble formation; namely, a significant increase in the ratio of the number of days with positive returns to the number of days with negative returns for the 4 months preceding the peak of a bubble, as well as abnormally high returns for the 4 months preceding the peak of a bubble.

### 3.2 Property 2: Peak rises more than 10% above +1 SD trend

We plot the time series for the three bubbles examined in this paper. To construct these figures, we choose a low point in the preceding dominant upward trend; that is, 14 July 1995 in Figure 1a for the 1997 bubble, 31 August 1998 in Figure 1b for the dot-com bubble and 5

TABLE 2
Volatility of log returns

| 1997 bubble | | Dot-com bubble | | 2007 bubble | |
|---|---|---|---|---|---|
| HIS | | Nasdaq | | HSI | |
| Period | Volatility of log return | Period | Volatility of log return | Period | Volatility of log return |
| 17 July 1995 to 29 April 1997 | 0.01 | 31 August 1998 to 4 January 2000 | 0.018 | 13 June 2005 to 11 June 2007 | 0.009 |
| 10 February 1997 to 7 August 1997 | 0.012 | 4 January 2000 to 10 March 2000 | 0.024 | 11 June 2007 to 30 October 2007 | 0.017 |

*Notes*: The table shows the volatility of stock returns before and during the bubble formation. HSI, Hang Seng Index.

TABLE 3
Summary statistics of returns

| Statistic | 1997 bubble (HSI) | Dot-com bubble | 2007 bubble |
|---|---|---|---|
| Period | 1995–1998 | 1998–2002 | 2007–2009 |
| $N$ | 764 | 1010 | 764 |
| Mean | −0.0005 | −0.0001 | −0.001 |
| Median | 0.0004 | 0.0015 | 0 |
| Maximum | 0.17 | 0.13 | 0.13 |
| Minimum | −0.15 | −0.1 | −0.14 |
| Variance | 0.0004 | 0.0006 | 0.0007 |
| Skewness | 0.21445 | 0.14773 | 0.1523 |
| Kurtosis | 15.45 | 1.49 | 4.63 |
| Jarque–Bera test | 4,940.102158 | 99.62794074 | 87.53151693 |
| Runs test | <0.0001*** | 0.592 | <0.0001*** |
| Ljung–Box–Pierce Q statistics Q(12) | 0.165 | 0.042 | 0.25 |

*Notes*: ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$. HSI, Hang Seng Index.

March 2007 in Figure 1c for the 2007 bubble. Thereafter, we obtain the prediction price for a certain day by regressing stock price at time $t$ using the data from the starting point to time $t-1$. In order to do so for each time $t$, we construct the moving linear regression line.

For the 1997 bubble, on 7 August 1997, the HSI reaches its peak of 16,673, which is far beyond the +1 SD prediction line by 10%. As for the dot-com bubble, the rise is more pronounced, with the NASDAQ rising above the +1 SD prediction line by more than 17% on 10 March 2000. A similar result is seen in the 2007 case. On 30 October 2007, the HSI reaches its peak of 31,638.22, which is far above the +1 SD prediction line, by 11%.

Hence, the peak of the index increases by more than 10% above the +1 SD trend line in two of the bubbles.

### 3.3 Property 3: Increase in volatility

The third property associated with the formation of a bubble is an increase in the volatility of stock returns, where returns are measured as continuously compounded log returns. Volatility is defined simply as the standard deviation of log returns for a specified period. During a bubble formation, prices rise beyond their fundamental value and are no longer driven by objective new information, and, hence, are expected to be more volatile than during normal periods. This is consistent with tests on volatility to detect systematic departure of stock prices from fundamental values.

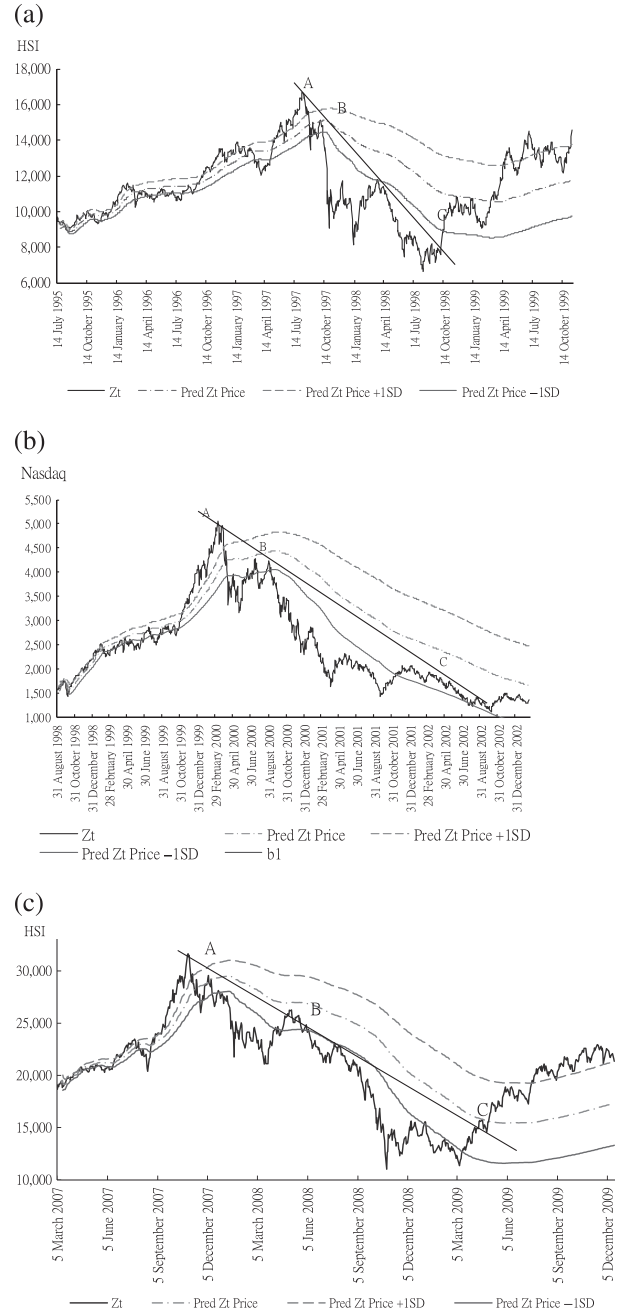


FIGURE 1. (a) Time-series plot of Hang Sang Index with prediction for 1997 bubble, (b) time-series plot of Nasdaq with prediction for dot-com bubble and (c) time-series plot of Hang Seng Index with prediction for 2007 bubble
*Notes*: Zt denotes the stock index. Predict Zt Price is the predicted stock price from a linear regression. Pred Zt Price + 1 SD/−1 SD is the predicted stock price +1 SD/−1 SD away from the regression price

For the 1997 bubble, the volatility (the standard deviation of the log returns for the previous 100 days) is as low as 0.008 on 16 August 1996 and increases to 0.018 on 7 October 1997, representing an increase of 125%. For the dotcom bubble, the volatility increases from 0.02 on 25 January 1999 to 0.034 on 2 June 2000, representing an increase of 70%. The increase is more pronounced for the subprime bubble, with the volatility increasing from 0.006 on 8 August 2005 to as high as 0.02 on 21 November 2007, representing an increase of over 233% (refer to Fig. 2a–c for time-series plots of volatility for the three periods).

### 3.4 Property 4: Falling below the −1 SD prediction line

Referring to Figure 1, signalling the bursting of the 1997 bubble is the index dropping below the −1 SD trend line on 9 October 1997. Thereafter, the HSI falls by 37% for the 19 days after the HSI drops below the −1 SD trend line. In the following year, the index drops by 53%, which signals the beginning of a long and deep recession. For the dot-com bubble (Fig. 2), Nasdaq drops below the trend line on 11 September 2000. Thereafter, the index falls from 4048 to 3075 on 12 October 2000, representing a decrease of 32% in just 1 month, and the index drops by 58% for the 6 months after the index crossed the −1 SD trend line. For the 2007 bubble (Fig. 3), the HSI drops below the trend line on 21 November 2007. Subsequently, 2.5 months later, the HSI drops from 27,616 on 9 January 2008 to 21,758 on 22 January 2008, representing a decrease of over 20% in just 13 days. In the year after the index drops below the −1 SD trend line, the index drops by 59%, which is even larger than the 1997 bubble.

Having identified the patterns in stock prices associated with the formation and bursting of bubbles, in the following we suggest a trading rule to profit from bubbles, and then examine different *TA* strategies to investigate whether this trading rule can help investors generate greater profits than without the trading rule.

### 3.5 Trading rule condition for a period of no less than 4 months (for points 1 to 3)

**1** The percentage of the number of days with positive returns minus the percentage of the number of days with negative returns increases by more than 7 percentage points.
**2** The annualized return for the period increases over 100%.
**3** The peak of the stock price rises above the +1 SD trend line by more than 10%.
**4** There is a greater than 70% increase in volatility (i.e. the standard deviation of the previous 100-day log returns).

If the above four conditions occur, then we suggest turning to *MA* short strategies when the stock price drops below the stock price regression line, until the stock price breaks a dominant downward trend.

## 4. Technical indicators

Moving average (*MA*) is the most commonly used trend indicator. There are many studies regarding the performance of *MA*, but the findings are not consistent. For example, Brock *et al.* (1992) show that *MA* significantly outperforms a cash benchmark when applied to the Dow Jones Industrial Average. However, Ready (1997) finds that, apart from the earliest sub-period (1970–1974), *MA* generally underperforms the buy-and-hold strategy. Wong *et al.* (2003)

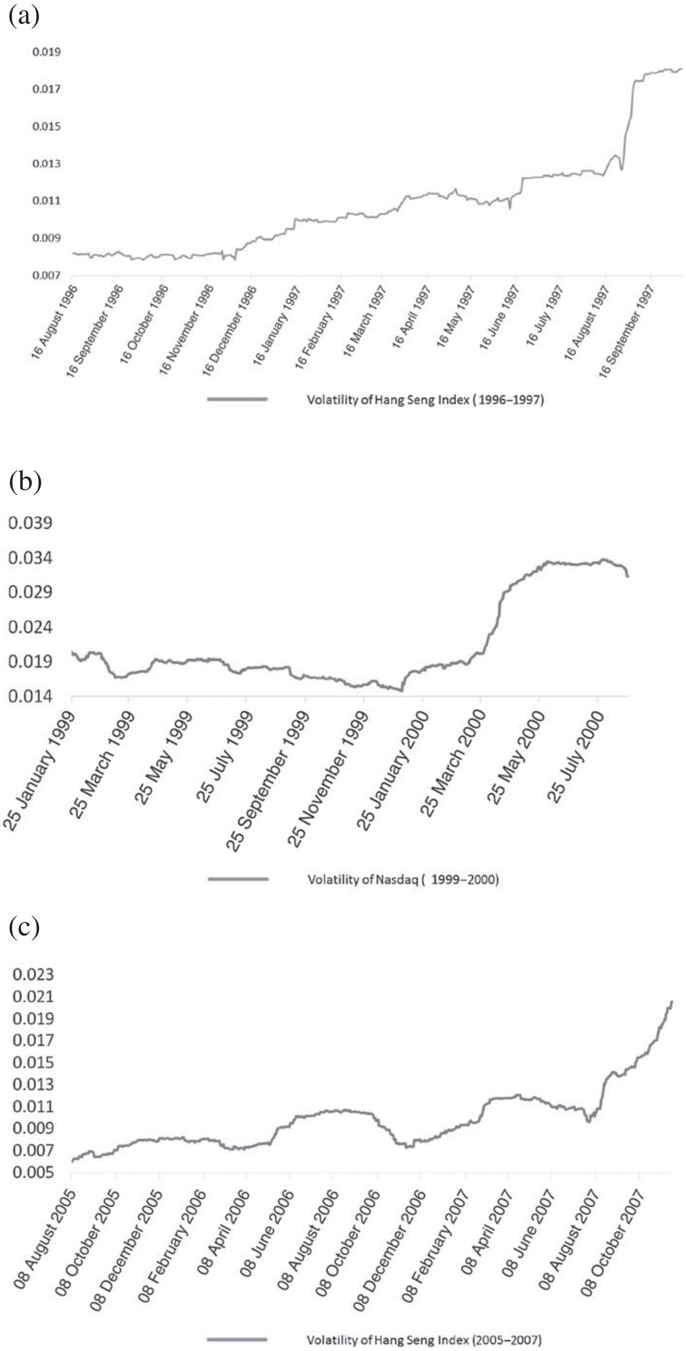


FIGURE 2. (a) Time-series plot of volatility of log returns of Hang Seng Index for 1997 bubble (the volatility increases from 0.008 on 16 August 1996 to 0.018 on 7 October 1997 (+125%)), (b) time-series plot of volatility of log returns of Nasdaq for dot-com bubble (the volatility increases from 0.02 on 25 January 1999 to 0.034 on 2 June 2000 (+70%)) and (c) time-series plot of volatility of log returns of Hang Seng Index for 2007 bubble (the volatility increases from 0.006 on 8 August 2005 to 0.02 on 21 November 2007 (+233%))

support the usefulness of the *MA* strategy. In contrast, Fong and Yong (2005) examine various *MA* rules and conclude there is no evidence of significant trading profits.

In this paper, we adopt the *MA* strategy to examine whether we can profit from the bubbles we study in the paper by investigating the following *MA* rules: simple moving average (*MA*), simple exponential moving average (*EMA*) and dual moving average (*DMA*). Readers may refer to Chan *et al.* (2014) for more information on the *MA* strategy. These strategies are described briefly below.

### 4.1 Simple moving average

The $n$-day simple moving average (*MA*) at time $t$, denoted by $MA_{t,n}$, is given by:

$$MA_{t,n} = \frac{1}{n}\sum_{i=t-n}^{t-1} C_i \ , \tag{1}$$

where $C_i$ is the closing price at time $i$. A moving average changes in response to the addition of a new period and the shedding of the oldest period. As the calculation continues, the $n$-day moving average increases when the closing price moves upwards as the added value is larger than the deleted value. In a simple *MA* procedure, a buy signal is generated when the closing price rises above *MA* and a sell signal is generated when the close falls below *MA*.

As moving averages are lagging indicators, they are trend following. If a clear trend exists, this method should work adequately. However, if the market is moving sideways or if there is excessive volatility, there could be many false signals. In such cases, Bollinger Bands and the *MA* Channels may be better trading tools than the use of moving averages (Leung and Chong, 2003).

### 4.2 Exponential moving average

To reduce the lag effect from the “outdated” data in simple moving averages, the exponential moving average strategy has been developed. The $n$-day exponential moving average (*EMA*) at time $t$, denoted by $EMA_{t,n}$, is defined as:

$$EMA_{t,n} = \alpha C_t + (1-\alpha) EMA_{t-1,n} \tag{2}$$

with $EMA_{1,n} = C_1$. In Equation (2), $\alpha = 2/(n+1)$. In addition, the first few $EMA_{t,n}$ values will be deleted so that the initial value for $EMA_{t,n}$ will not affect $EMA_{t,n}$.

Exponential moving averages reduce the lag effect from the “outdated” data by assigning greater weight to more recent prices. The smoothing constant $2/(n+1)$ in Equation (2) works as the weight that applies to the most recent price depending on the length of the moving average. The shorter is the exponential moving average, the greater is the weight that will be assigned to the most recent price. For example, a 10-period exponential moving average would weight the most recent price 18.18%, and a 20-period exponential moving average would weight the most recent price 9.52%.

An *EMA* will react faster to recent price changes than will a simple moving average. The *EMA* formula works by weighting the difference between the price in the current period and the *EMA* in the previous period, and then updating the result of the *EMA* in the previous

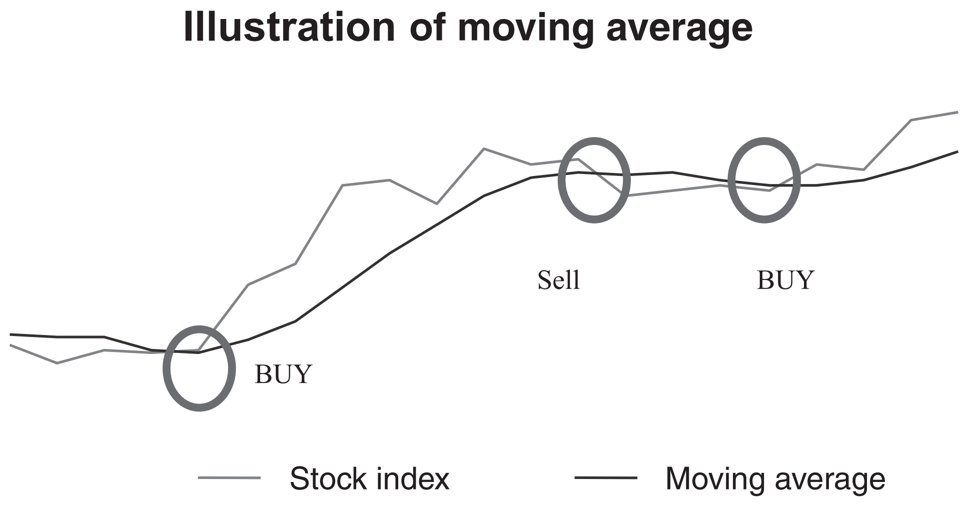


FIGURE 3. Illustration of moving average

period. The diagram given below shows the formation of the buy and sell signals by the use of the *MA* strategy (either *MA* or *EMA*).

A buy signal is generated when the closing price passes the *EMA* from below, and a sell signal is generated when the closing price passes the *EMA* from above. As in the case of *MA*, the effectiveness of *EMA* is also undermined by excessive volatilities in stock prices.

### 4.3 Dual moving average

Another commonly used trading rule (Brock *et al.*, 1992) is the dual *MA* (*DMA*) strategy, denoted by *DMA*($n$,$m$), that consists of two *MA*: a "short" $n$-day *MA*, $MA_{t,n}$, and a "long" $m$-day *MA*, $MA_{t,m}$, with $m > n$. The rule generates a buy (sell) signal when the short *MA* rises above (falls below) the long *MA*. The common *DMA* rules are 1–5, 1–200, 5–10, 5–20, 5–30 and 5–200. When the *DMA* is formed by two *EMA*, we call it a dual exponential moving average (*DEMA*), denoted by *DEMA*($n$,$m$).

As in the case of *DMA*, there are two *EMA*: a "short" $n$-day *EMA*, $EMA_{t,n}$, and a "long" $m$-day *EMA*, $EMA_{t,m}$, with $m > n$. The rule for the *DEMA* signals is the same as that of the *DMA*. The 5–20 day and 5–30 day *DMA* and *DEMA* strategies are examined in the present paper.

Unlike simple *MA* and *EMA*, *DMA* is less affected by excess volatilities on certain days due to the smoothing effect of the short *MA*.

## 5. Strategies with and without trading rules

The data used in this paper are the daily closing values of the Nasdaq and the HSI extracted from Yahoo.com/finance. Three periods, namely, NASDAQ 31 August 1998 to 9 September 2002, HSI 14 July 1995 to 31 August 1998, and HSI 5 March 2007 to 31 March 2009, will be used to examine different trading strategies. Each period will be further divided into two periods; namely, before and after the bursting of bubbles, which are identified by the times when the stock price passes below the moving regression line from the peak. The six periods are: NASDAQ 31 August 1998 to 12 April 2000, NASDAQ 12 April 2000 to 9 September 2002, HSI 14 July 1995 to 1 September 1997, HSI 1 September 1997 to 31 August 1998, HIS 5 March 2007 to 15 November 2007, and HIS 15 November 2007 to 31 March 2009.

Under our trading rule, we adopt the *MA* long only strategy during bubble formation, and for the period after the stock price dropped below the stock price regression line signalling the bursting of the bubble, we will adopt the *MA* short only strategy. To demonstrate the effectiveness of the proposed bubble detection signals, we will compare the abovementioned strategy with the trading rule with the *MA* strategy without a trading rule. Without a trading rule, we will adopt the *MA* long and short strategy throughout the whole period.

As a strategy under the proposed trading rule, the *MA* short strategy is adopted when the four properties mentioned in Section 3 are satisfied, starting when the stock indexes fall below the moving linear regression lines from their peaks, until the end of the bear run. In Figure 1a, for the 1997 bubble, a trend line is drawn to pass through A, B and C, so that the end point of the bear run is around 31 August 1998. In Figure 1c, for the 2007 bubble, a trend line is drawn to pass through A, B and C, so that the end point is around 31 March 2009. For the dot-com bubble, as shown in Figure 1b, a trend line is drawn to pass through A, B and C, so that the end point for the bear run is around 9 September 2002. After the end point C in Figure 1a–c, the stock indexes turn bull, and the short strategy is no longer profitable.

### 5.1 Hypothesis testing for long strategies

The closing prices of the indexes are used to compute the daily returns, $r_t$, such that $r_t = 100*Ln\ (C_t/C_{t-1})$, where $C_t$ is the closing price of the index on day $t$. Suppose at time $t$ there is a buy (sell) signal, and at time $t+n_t$ there is a sell (buy) signal, and form the long (short) trading strategy. The aggregate return $S_{t,n_t}$ will be given as

$$S_{t,n_t} = \sum_{i=1}^{n_t} r_{t+i}. \tag{3}$$

Without loss of generality, we denote $S_{t,n_t}$ as $S_t$. Suppose we have the buy (sell) signals at $t_1$, $t_2, \ldots, t_m$, let $\Lambda = \{t_1, t_2, \ldots, t_m\}$, and define $\Omega$ to be the set of all these trading returns, such that $\Omega = \cup_{i \in \Lambda} I_i$, where the $\{I_i\}$ are the disjoint sets of returns generated by the $i$th buy (sell) signals (namely, buy (sell) at time $t_i$ and sell (buy) at time $t_i + n_i$). Let $n = N(\Omega)$ be the number of elements in the set $\Omega$, $r_\Omega$ be the vector of all returns in $\Omega$, and $1_\Omega$ be the $n \times 1$ vector of unit elements. Assume that the mean vector and covariance matrix of $r_\Omega$ are $\mu_\Omega$ and $\Sigma_\Omega$, respectively.

If $\Omega$ is the set of all the daily returns generated by buy signals, let $r_\Omega^{long}$, $\mu_\Omega^{long}$, $\Sigma_\Omega^{long}$ and $n_{long}$ correspond to $r_\Omega$, $\mu_\Omega$, $\Sigma_\Omega$ and $n$, respectively. Similarly, if $\Omega$ is the set of all the daily returns generated by sell signals, let $r_\Omega^{short}$, $\mu_\Omega^{short}$, $\Sigma_\Omega^{short}$ and $n_{short}$ correspond to $r_\Omega$, $\mu_\Omega$, $\Sigma_\Omega$ and $n$, respectively. $r_\Omega^{long}$ is the vector of daily returns for the long strategy generated by the indicator $MA_t$, while $r_\Omega^{short}$ is the vector of daily returns for the short strategy generated by the indicator. Furthermore, define $\mu_{long}$ and $\mu_{short}$ as the population means of daily returns generated by the buy and sell signals, respectively.

The null hypothesis:

$$H_{01}: \mu_{long} = 0 \text{ against } H_{11}: \mu_{long} > 0 \tag{4}$$

is tested for whether the return is profitable for the long strategy. In contrast, the null hypothesis:

$$H_{02} : \mu_{short} = 0 \text{ against } H_{12} : \mu_{short} < 0 \tag{5}$$

is tested for whether the return is profitable for the short strategy. Statistics applied to test whether the buy and sell signals generated by the family of *MA* yield significantly positive returns for either the long and short strategies are given by:

$$\begin{aligned} T &= \frac{1_\Omega^T r_\Omega}{\sqrt{1_\Omega^T \widehat{\Sigma}_\Omega 1_\Omega}} \\ \bar{r} &= 1_\Omega^T r_\Omega / n \quad , \end{aligned} \tag{6}$$

where $\bar{r}$, $r_\Omega$ and $\Sigma_\Omega$ are $\bar{r}_{long}$, $r_\Omega^{long}$ and $\Sigma_\Omega^{long}$, respectively, if it is used to test the null hypothesis in Equation (4), and are $\bar{r}_{short}$, $r_\Omega^{short}$ and $\Sigma_\Omega^{short}$, respectively, if it is used to test the null hypothesis in Equation (5).

We also report the mean return difference, also known as the buy–sell spread, between the long and short strategy.

The null hypothesis:

$$H_{03} : \mu = 0 \text{ against } H_{11} : \mu > 0,$$

where $\mu$ is the mean return of using both long and short strategies.

The *t*-statistic for testing whether using both the long and short strategies is profitable is given by:

$$T = \frac{\bar{r}_{long} - \bar{r}_{short}}{\sqrt{\sigma_{long}^2 / n_{long} + \sigma_{short}^2 / n_{short}}}. \tag{7}$$

The test statistic $T$ will be approximately distributed as $N(0,1)$ if $\mu$ ($\mu_{long}$ and $\mu_{short}$) is 0. In estimating $\widehat{\Sigma}_\Omega$, we set the entries to be zero if they are not significant at the 5% level.

For example, for the Taiwan stock market data for the simple *MA*(5) long strategy, the only significant autocorrelations are at lags 1, 3 and 4, with values of −0.078, −0.090 and −0.073, respectively. Thus, in testing this rule for Taiwan, we set all entries to be zero except the autocorrelations at lags 1, 3 and 4.

As $n$ is very large, $T$ will approach the standard normal distribution asymptotically. Therefore, the profit generated by using the $MA_t$ strategy is significantly greater than zero if:

$$\begin{cases} T > z_\alpha & \text{in a long position} \\ T < -z_\alpha & \text{in a short position} \end{cases}, \tag{8}$$

where $z_\alpha$ is the critical value, such that $\alpha = P(Z > z_\alpha)$ and $Z$ follows the standardized normal distribution.

Nonetheless, it is well known that the daily return is not i.i.d., and is also not normal (see e.g. Fama, 1965; Fama and French, 1988). It is useful to refer to Lo and MacKinlay (1990) for the violation of the normality assumption, and Conrad and Kaul (1988) for the violation of the independence assumption for daily returns. To accommodate the possibility that the central limit theorem is not applicable for our data set, we use a bootstrap technique (Hall, 1992) in the empirical analysis to check for normality. The results obtained from the bootstrap approach are very close to those obtained by assuming the statistic $T$ to approach the standard normal distribution. Therefore, we report only the results obtained by the latter method.

To check whether any of the moving average approaches significantly outperforms the *BH* strategy, we let $\bar{r}_{BH}$ and $\mu_{BH}$ be the sample and population means of daily returns, respectively, for the *BH* strategy, and use $\bar{r}$ and $n$ as defined in Equation (6). Recall that $\bar{r}$ is equal to $\bar{r}_{long}$ if $\Omega$ is generated by the buy signals, and is equal to $\bar{r}_{short}$ if $\Omega$ is generated by the sell signals. Let $\mu$ ($\mu_{long}$ and $\mu_{short}$) be the mean and $\sigma^2$( $\sigma^2_{long}$ and $\sigma^2_{short}$) the variance of $r_t$, respectively. Then, we have $\sigma^2 = 1^T_\Omega \Sigma_\Omega 1_\Omega / n$, where $1^T_\Omega \Sigma_\Omega 1_\Omega$ is defined in Equation (6). To check whether any of the moving average approaches significantly outperforms the *BH* strategy, it is necessary to test whether the return, $\mu_{long}$, generated by the long strategy using the *MA* family is significantly greater than the return, $\mu_{BH}$, using the *BH* strategy.

The analysis described above is used to test the null hypothesis:

$$H_{03} : \mu_{long} = \mu_{BH} \ \text{ against } \ H_{13} : \ \mu_{long} > \mu_{BH}. \tag{9}$$

Similarly, the null hypothesis:

$$H_{04} : \mu_{short} = \mu_{BH} \ \text{ against } \ H_{14} : \mu_{short} < \mu_{BH} \tag{10}$$

tests whether the return, $\mu_{short}$, generated by the short strategy using the *MA* family is significantly greater than the return, $\mu_{BH}$, obtained from using the *BH* strategy.

Let $R = (\bar{r}, \bar{r}_{BH})^T$, $\Sigma$ represents the covariance matrix of $R$, and introduce the following test statistic to test whether a long or short strategy using the buy and sell signals generated by the *MA* family significantly outperforms the *BH* strategy:

$$T' \approx \frac{a^T R}{\sqrt{a^T \Sigma a}}, \tag{11}$$

where $a = (1, -1)^T$.

The statistic $T'$ should approach the standard normal distribution by virtue of the central limit theorem as the sample size is very large for the data sets used in the paper. As discussed above, to accommodate the possibility that the central limit theorem is not effective for our data set, we use a bootstrap technique in the empirical analysis to check for normality. The results obtained from the bootstrap approach are very close to those obtained by assuming that the statistic T approaches to the standard normal distribution. Thus, we only report the results obtained by the latter method.

The buy/sell strategy is significantly profitable if:

$T > z_\alpha$ in a long position
$T < -z_\alpha$ in a short position.

The buy/sell strategy is significantly better than the buy/hold strategy if:

$T' > z_\alpha$ for both long and short positions.

The statistics $T$ and $T'$ will be applied to the aforementioned six periods for the three bubble periods.

### 5.2 Wealth analysis

In addition to evaluating the performance of these *TA* strategies, we have also created a portfolio with an initial amount of \$1m local currency to compare the performance of different strategies. As trading costs are not negligible in buy/sell strategies, it is necessary to take them into account. The cost of trading varies across countries. For Hong Kong, investors pay a stamp duty of 0.1%, as well as a small amount to cover a commission, a transaction levy, a transfer fee, a trading fee and a transfer deed fee. For the USA, the trading fee normally ranges from US\$9.99 to US\$19.99. For simplicity, we will impose a transaction cost of 0.1% in both cases.

## 6. Empirical results

First, we describe market returns for the full three periods; namely, the dot-com bubble, the Asian financial crisis and the subprime crisis. These are the returns that investors would receive from a buy-and-hold strategy. Hence, the *t*-value could be used to test whether the buy/hold strategy could generate significant returns for the three periods.

As shown in Table 4 for all three periods, the *BH* strategy did not generate significantly positive returns in any of the three periods, and actually gives negative returns. Hence, it is necessary to find strategies other than a buy/hold strategy to generate profits from the bull and bear runs. As will be shown below, *TA* strategies not only generate significantly positive returns, but could also generate a significant amount of wealth from active buying and selling strategies.

### 6.1 Returns analysis from technical analysis strategies under our trading rules

Under a trading rule, a long and short strategy is adopted during a bubble formation, and a short strategy is adopted after the stock price passes through the stock price regression line from the peak. Tables 5–7 report the average daily returns, and the corresponding test statistics, *T*, under the trading rule for the three periods. The difference between the returns from the *TA* and *BH* strategies is also computed, showing the test statistics $T'$, as well as the corresponding *p*-values. In addition, the total numbers of holding days (*N*) generated by different strategies are also shown.

In Table 5, it is found that most *MA* rules generate positive returns that are significant at the 5% level, so we can conclude that all *MA* rules provide positive returns for the period of the Asian financial crisis. The difference between the returns generated by the *MA* rule and *BH*

TABLE 4
Returns from buy-and-hold strategy

| Index | Period | *N* | Mean (*R*(*bh*)) (%) | Variance (%) | *T* | *p*-value |
|---|---|---|---|---|---|---|
| HIS | 1995–1998 | 764 | −0.05 | 0.04 | −0.68 | 0.25 |
| Nasdaq | 1998–2002 | 1010 | −0.01 | 0.06 | −0.18 | 0.43 |
| HIS | 2007–2009 | 764 | −0.10 | 0.07 | −1.04 | 0.15 |

*Notes*: Buy and hold strategies give negative returns for all three periods where *bh* refers to buy and hold. *N* denotes the number of days during each period. *T* is the standard *t*-statistic of whether the mean returns from the buy/hold strategy is significantly different from zero. HSI, Hang Seng Index.

TABLE 5
Hang Seng Index 1995–1998 testing daily returns of the technical analysis strategy (under trading rule)

| Rule | N | R (%) | T | p-value | R-R(bh) (%) | T′ | p-value |
|---|---|---|---|---|---|---|---|
| *MA*(5) | 655 | 0.25 | 3.15 | 0.001*** | 0.30 | 2.78 | 0.003*** |
| *MA*(10) | 663 | 0.18 | 2.36 | 0.009*** | 0.23 | 2.19 | 0.014** |
| *MA*(20) | 652 | 0.19 | 2.41 | 0.008*** | 0.24 | 2.23 | 0.013** |
| *MA*(30) | 654 | 0.12 | 1.54 | 0.062* | 0.17 | 1.60 | 0.055* |
| *MA*(50) | 628 | 0.14 | 1.76 | 0.039** | 0.19 | 1.76 | 0.039** |
| *DMA*(5,20) | 648 | 0.18 | 2.28 | 0.011** | 0.23 | 2.14 | 0.016** |
| *DMA*(5,30) | 652 | 0.10 | 1.28 | 0.100* | 0.15 | 1.41 | 0.080* |
| *EMA*(5) | 660 | 0.22 | 2.83 | 0.002*** | 0.27 | 2.54 | 0.006*** |
| *EMA*(10) | 672 | 0.18 | 2.35 | 0.010* | 0.23 | 2.18 | 0.015** |
| *EMA*(20) | 656 | 0.17 | 2.14 | 0.016 | 0.22 | 2.04 | 0.021** |

*Notes*: $***p < 1\%$, $**p < 5\%$, $*p < 10$. $N$ is the number of days during each period and $bh$ refers to buy and hold, $R\text{-}R(bh)$ is $R$ in Equation (11), $T$ and $T'$ are the $t$-statistics in Equations (6) and (11), respectively.

TABLE 6
Nasdaq 1998–2002 testing daily returns of the technical analysis strategy (under trading rule)

| Rule | N | R (%) | T | p-value | R-R(bh) (%) | T′ | p-value |
|---|---|---|---|---|---|---|---|
| *MA*(5) | 728 | 0.15 | 1.68 | 0.046** | 0.17 | 1.40 | 0.081* |
| *MA*(10) | 765 | 0.15 | 1.66 | 0.048** | 0.16 | 1.37 | 0.085* |
| *MA*(20) | 758 | 0.19 | 2.12 | 0.017** | 0.20 | 1.72 | 0.042** |
| *MA*(30) | 770 | 0.19 | 2.12 | 0.017** | 0.20 | 1.71 | 0.043** |
| *MA*(50) | 723 | 0.16 | 1.71 | 0.044** | 0.17 | 1.42 | 0.078* |
| *DMA*(5,20) | 757 | 0.13 | 1.45 | 0.074* | 0.14 | 1.21 | 0.113 |
| *DMA*(5,30) | 765 | 0.20 | 2.22 | 0.013** | 0.21 | 1.79 | 0.037** |
| *EMA*(5) | 736 | 0.15 | 1.62 | 0.052* | 0.16 | 1.35 | 0.088* |
| *EMA*(10) | 745 | 0.19 | 2.11 | 0.018** | 0.20 | 1.72 | 0.043** |
| *EMA*(20) | 771 | 0.21 | 2.38 | 0.009*** | 0.22 | 1.91 | 0.028** |

*Notes*: $***p < 1\%$, $**p < 5\%$, $*p < 10$. $N$ is the number of days during each period and $bh$ refers to buy and hold, $R\text{-}R(bh)$ is $R$ in Equation (11), $T$ and $T'$ are the $t$-statistics in Equations (6) and (11), respectively.

TABLE 7
Hang Seng Index 2007–2009 testing daily returns of the technical analysis strategy

| Rule | N | R (%) | T | p-value | R-R(bh) (%) | T′ | p-value |
|---|---|---|---|---|---|---|---|
| *MA*(5) | 363 | 0.16 | 1.17 | 0.122 | 0.26 | 1.55 | 0.061* |
| *MA*(10) | 367 | 0.23 | 1.64 | 0.051* | 0.32 | 1.93 | 0.027** |
| *MA*(20) | 372 | 0.23 | 1.65 | 0.050** | 0.32 | 1.94 | 0.026** |
| *MA*(30) | 363 | 0.31 | 2.20 | 0.014** | 0.40 | 2.40 | 0.008*** |
| *MA*(50) | 375 | 0.25 | 1.80 | 0.036** | 0.34 | 2.06 | 0.020** |
| *DMA*(5,20) | 371 | 0.24 | 1.78 | 0.037** | 0.34 | 2.05 | 0.020** |
| *DMA*(5,30) | 358 | 0.25 | 1.80 | 0.036** | 0.35 | 2.07 | 0.019** |
| *EMA*(5) | 368 | 0.20 | 1.48 | 0.070** | 0.30 | 1.80 | 0.036** |
| *EMA*(10) | 381 | 0.21 | 1.56 | 0.059* | 0.31 | 1.87 | 0.031** |
| *EMA*(20) | 408 | 0.23 | 1.74 | 0.041** | 0.33 | 2.01 | 0.022** |

*Notes*: $***p < 1\%$, $**p < 5\%$, $*p < 10$. $N$ is the number of days during each period and $bh$ refers to buy and hold, $R\text{-}R(bh)$ is $R$ in Equation (11), $T$ and $T'$ are the $t$-statistics in Equations (6) and (11), respectively.

strategy are all positive, with most being significant at the 5% level. Hence, we conclude that *MA* rules outperform the *BH* strategy for the period of the Asian financial crisis.

From Table 6, we find that the average daily returns from the *MA* strategy under our trading rule are all positive, and most are significant at the 5% level. Hence, we conclude that the *MA* rules provide significantly positive returns for the period of the dot-com bubble. Moreover, the difference between the average daily return generated by the *MA* rules and the *BH* strategy are all positive, and all are significant at the 10% level. Hence, we conclude that all the *MA* rules outperform the *BH* strategy for the period of the dot-com bubble.

As can be seen in Table 7, all the *MA* rules generate positive returns, and most are significant at the 10% level, so we can conclude that all the *MA* rules generate positive returns for the period subprime bubble. The difference between the returns from all the *MA* rules and *BH* strategy are all positive, and all are significant at the 10% level, so we conclude that all *MA* rules outperform the *BH* strategy for the period of the subprime bubble.

### 6.2 Technical analysis strategies without our trading rules

In Tables 8–10, we also report the returns from *TA* strategies without signalling the bubble; that is, we adopt long and short strategies throughout the entire three periods. In Table 8,

TABLE 8
Hang Seng Index 14 July 1995 to 31 August 1998 for long and short

| Rule | *N* | *R* (%) | *T* | *p*-value | *R-R*(*bh*) (%) | *T′* | *p*-value |
|---|---|---|---|---|---|---|---|
| *MA*(5) | 754 | 0.20 | 2.75 | 0.003*** | 0.25 | 2.43 | 0.008*** |
| *MA*(10) | 754 | 0.14 | 1.92 | 0.027** | 0.10 | 0.97 | 0.165 |
| *MA*(20) | 732 | 0.14 | 1.89 | 0.029** | 0.10 | 0.97 | 0.167 |
| *MA*(30) | 729 | 0.07 | 0.95 | 0.172 | 0.03 | 0.29 | 0.386 |
| *MA*(50) | 682 | 0.11 | 1.44 | 0.075* | 0.07 | 0.66 | 0.253 |
| *DMA*(5,20) | 731 | 0.14 | 1.89 | 0.029** | 0.10 | 0.97 | 0.167 |
| *DMA*(5,30) | 727 | 0.06 | 0.81 | 0.209 | 0.02 | 0.19 | 0.423 |
| *EMA*(5) | 753 | 0.18 | 2.47 | 0.007*** | 0.14 | 1.36 | 0.086* |
| *EMA*(10) | 757 | 0.14 | 1.93 | 0.027** | 0.10 | 0.97 | 0.165 |
| *EMA*(20) | 740 | 0.12 | 1.63 | 0.051* | 0.08 | 0.78 | 0.219 |

*Notes*: ***$p < 1\%$, **$p < 5\%$, *$p < 10$. *R* is return for long and short. Long and short strategies are adopted throughout the whole period, without our trading rule. *MA* families are able to generate significantly positive returns for the period Asian financial crisis. *N* is the number of days during each period and *bh* refers to buy and hold, *R-R*(*bh*) is *R* in Equation (11), *T* and *T′* are the *t*-statistics in Equations (7) and (11), respectively.

TABLE 9
Nasdaq 31 August 1998 to 9 September 2002 for long and short

| Rule | *N* | *R* (%) | *T* | *p*-value | *R-R*(*bh*) (%) | *T′* | *p*-value |
|---|---|---|---|---|---|---|---|
| *MA*(5) | 1004 | 0.06 | 0.76 | 0.22 | 0.07 | 0.67 | 0.25 |
| *MA*(10) | 1027 | 0.07 | 0.89 | 0.19 | 0.08 | 0.75 | 0.23 |
| *MA*(20) | 989 | 0.12 | 1.58 | 0.06* | 0.14 | 1.25 | 0.11 |
| *MA*(30) | 980 | 0.14 | 1.79 | 0.04** | 0.15 | 1.40 | 0.08** |
| *MA*(50) | 895 | 0.08 | 0.98 | 0.16 | 0.09 | 0.83 | 0.20 |
| *DMA*(5,20) | 987 | 0.05 | 0.69 | 0.24 | 0.07 | 0.62 | 0.27 |
| *DMA*(5,30) | 974 | 0.13 | 1.61 | 0.05* | 0.14 | 1.27 | 0.10* |
| *EMA*(5) | 1002 | 0.05 | 0.66 | 0.25 | 0.06 | 0.59 | 0.28 |
| *EMA*(10) | 991 | 0.09 | 1.20 | 0.12 | 0.11 | 0.98 | 0.16 |
| *EMA*(20) | 996 | 0.14 | 1.78 | 0.04** | 0.15 | 1.39 | 0.08* |

*Notes*: ***$p < 1\%$, **$p < 5\%$, *$p < 10$. *R* is return for long and short. Long and short strategies are adopted throughout the whole period. *N* is the number of days during each period and *bh* refers to buy and hold, *R-R*(*bh*) is *R* in Equation (11), *T* and *T′* are the *t*-statistics in Equations (7) and (11), respectively.

TABLE 10
Hang Seng Index 5 March 2007 to 31 March 2009 for long and short

| Rule | $N$ | $R$ (%) | $T$ | $p$-value | $R$-$R(bh)$ (%) | $T'$ | $p$-value |
|---|---|---|---|---|---|---|---|
| $MA(5)$ | 494 | 0.07 | 0.60 | 0.27 | 0.17 | 2.41 | 0.008*** |
| $MA(10)$ | 494 | 0.09 | 0.73 | 0.23 | 0.19 | 2.63 | 0.004*** |
| $MA(20)$ | 467 | 0.11 | 0.89 | 0.19 | 0.21 | 2.72 | 0.003*** |
| $MA(30)$ | 448 | 0.22 | 1.76 | 0.04** | 0.32 | 3.97 | <0.001*** |
| $MA(50)$ | 445 | 0.18 | 1.44 | 0.08 * | 0.28 | 3.44 | <0.001*** |
| $DMA(5,20)$ | 464 | 0.13 | 1.07 | 0.14 | 0.23 | 3.00 | 0.001*** |
| $DMA(5,30)$ | 446 | 0.15 | 1.17 | 0.12 | 0.24 | 3.03 | 0.001*** |
| $EMA(5)$ | 496 | 0.10 | 0.83 | 0.20 | 0.20 | 2.81 | 0.002*** |
| $EMA(10)$ | 498 | 0.06 | 0.54 | 0.29 | 0.16 | 2.33 | 0.010*** |
| $EMA(20)$ | 497 | 0.13 | 1.10 | 0.14 | 0.23 | 3.26 | 0.001*** |

*Notes*: ***$p < 1\%$, **$p < 5\%$, *$p < 10$. $R$ is $R$ for long and short. Long and short strategies are adopted throughout the whole period.

during the Asian financial crisis, most of the *MA* families were able to generate returns that are significant at the 10% level, with most also being significant at the 5% level. Hence, we conclude that the *MA* families are able to generate significantly positive returns for the period of the Asian financial crisis. However, the difference between the returns from long and short and *BH* strategies are not significant at the 10% level, so that we can conclude that long and short strategies are not able to beat the *BH* strategy for the period of the Asian financial crisis.

In Table 9, most of the *MA* families are not able to generate significantly positive returns for the period 31 August 1998–9 September 2002 for Nasdaq. Moreover, the difference between the long and short and *BH* strategies are not significant at the 10% level, so that we conclude that the *MA* families cannot beat the *BH* strategy for the period of the dot-com bubble. In Table 10, most of the *MA* families did not generate returns that are significant at the 10% level. However, the difference between returns from the long and short and *BH* strategies are significant at the 1% level, so we can conclude that the long and short strategies are able to beat the *BH* strategy for the sample given in the subprime crisis.

Table 11 provides a summary of comparisons between strategies with and without the trading rules.

TABLE 11
Summary table: With trading rule versus without trading rule

| | | Financial crises | | |
|---|---|---|---|---|
| | | Asian financial crisis | Dot-com bubble | Subprime crisis |
| With trading rule | Most *MA* can generate significant positive return. | True | True | True |
| | Most *MA* can significantly beat *BH* strategy. | True | True | True |
| Without trading rule | Most *MA* can generate significant positive return. | True | False | False |
| | Most *MA* can significantly beat *BH* strategy. | False | False | False |

*Notes: BH*, buy-and-hold; *MA*, moving average.

### 6.3 Wealth analysis with and without our trading rules

To complete the empirical analysis, we establish a portfolio with an initial amount of $1m in the beginning of the three periods; namely, the Asian financial crisis, the dot-com bubble and the subprime crisis. With a trading rule, during the bull run (from the beginning to the point where the stock price dropped below the moving regression line from the peak), we adopt

TABLE 12
(a) HSI 14 July 1995 to 31 August 1998 Wealth from TA strategy (with 0.1% transaction costs). (b) NASDAQ 31 August 1998 to 9 September 2002 qealth from TA strategy (with 0.1% transaction costs). (c) HSI 5 March 2007 to 31 March 2009 wealth from TA strategy (with 0.1% transaction costs)

| Rule | Under trading rule | Without trading rule | |
|---|---|---|---|
| | Wealth (0.1% cost) | Wealth (0.1% cost) | Outperformed by (%) |
| (a) | | | |
| *BH* | 0.62 | | |
| *MA*(5) | 2.52 | 2.29 | 10.00 |
| *MA*(10) | 2.21 | 1.99 | 10.95 |
| *MA*(20) | 2.32 | 2.12 | 9.43 |
| *MA*(30) | 1.67 | 1.42 | 17.69 |
| *MA*(50) | 1.84 | 1.77 | 4.20 |
| *DMA*(5,20) | 2.37 | 2.21 | 7.24 |
| *DMA*(5,30) | 1.61 | 1.39 | 15.58 |
| *EMA*(5) | 2.34 | 2.12 | 10.38 |
| *EMA*(10) | 2.19 | 1.97 | 11.38 |
| *EMA*(20) | 2.10 | 1.88 | 11.90 |
| (b) | | | |
| *BH* | 0.86 | | |
| *MA*(5) | 1.71 | 1.07 | 60.15 |
| *MA*(10) | 1.95 | 1.30 | 49.84 |
| *MA*(20) | 2.48 | 2.17 | 14.27 |
| *MA*(30) | 2.43 | 2.32 | 4.92 |
| *MA*(50) | 2.16 | 1.77 | 22.27 |
| *DMA*(5,20) | 1.93 | 1.49 | 29.68 |
| *DMA*(5,30) | 2.84 | 2.48 | 14.31 |
| *EMA*(5) | 1.70 | 1.01 | 67.90 |
| *EMA*(10) | 2.34 | 1.61 | 45.30 |
| *EMA*(20) | 2.78 | 2.39 | 16.42 |
| (c) | | | |
| *BH* | 0.24 | | |
| *MA*(5) | 1.30 | 1.01 | 28.76 |
| *MA*(10) | 1.76 | 1.29 | 36.29 |
| *MA*(20) | 1.88 | 1.48 | 26.77 |
| *MA*(30) | 2.25 | 2.08 | 8.23 |
| *MA*(50) | 1.95 | 1.76 | 10.80 |
| *DMA*(5,20) | 2.00 | 1.66 | 20.27 |
| *DMA*(5,30) | 1.97 | 1.72 | 14.33 |
| *EMA*(5) | 1.54 | 1.17 | 31.64 |
| *EMA*(10) | 1.67 | 1.13 | 47.77 |
| *EMA*(20) | 1.92 | 1.60 | 20.15 |

*Notes*: A portfolio of $1m is set up at the beginning of the three periods. Transaction costs of 0.1% are considered. Under our trading rule, a long and short strategy is adopted from the low point of the bull market up to the point when the stock index dropped from its peak to below the predicted stock index Pred Zt Price (Figures 1–3). Thereafter, a short strategy is taken until the stock price broke the downward trend ABC by passing through point C. Without a trading rule, long and short strategies are adopted throughout the whole period. As Table 12a–c shows, the bubble detection signals enable investors to generate greater wealth from 7 to 68%. BH, buy-and-hold; *EMA*, exponential moving average; *DMA*, dual moving average; HIS, Hang Seng Index; *MA*, moving average; *TA*, technical analysis.

the long and short only strategies using the *MA* family. Thereafter, we adopt a short only strategy using the *MA* family. For comparison, we also establish the same portfolio for the *BH* strategy. The results are shown in Table 12a–c.

To demonstrate the effectiveness of our bubble detection signals, we also show wealth calculated without a trading rule. As given in Tables Table 12a–c, *MA* strategies with a trading rule are able to beat the *MA* strategies without a trading rule by 4 to 68%.

Comparing the *MA* strategies with and without our trading rules, given a 0.1% transaction cost scenario, under our trading rule the *MA* strategies are able to outperform the *MA* strategies without a trading rule by 4 to 68%. Hence, we conclude that our bubble detection signals are able to help investors generate greater wealth.

In Table 12a, the most profitable strategies are *MA*5, 10 and 20, *DMA*(5, 20) and *EMA*5 with a trading rule. From an initial amount of $1m, the investment grew to more than $2.2m in just 3 years. In Table 12b, the most profitable strategies are *MA*20, *DMA*(5,30) and *EMA*20, whereby a $1m initial investment has increased to more than $2.4m in just 4 years. In Table 12c, the most profitable strategies are *MA*20, *MA*30, *DMA*(5,20), *DMA*(5,30) and *EMA*20, such that an initial investment of $1m grew to more than $1.8m in just 2 years.

In Tables 12a–c, we also report the wealth generated from *TA* strategies without a trading rule; that is, we adopt long and sell strategies throughout the three periods. In Table 12a, the greatest wealth of up to $2.29m is generated from *MA*(5), which is 10% smaller than the $2.52m generated from the same *TA* strategies under our trading rule. In Table 12b, the greatest wealth up to 2.39m is generated from *EMA*(20), which is 16% below the $2.78m wealth generated from a trading rule and adopted short strategies after the bubble burst. In Table 12c, the greatest wealth is generated from *MA*30, generating $2.08m, compared with $2.25m by the same *TA* strategies under our trading rule.

In short, all *MA* strategies can generate significant returns, and all are able to outperform the *BH* strategies. In all three cases, *MA*20 consistently produces a significant amount of wealth using long strategies during bull runs and short strategies during bear runs. Moreover, comparing the *TA* strategies with and without our trading rules, the former is able to beat the latter substantially, so that the signalling of a bubble is able to help investors generate significant wealth.

## 7. Conclusion

In summary, there are four primary properties associated with the formation and bursting of bubbles. The first three are about the formation of bubbles, and the fourth one signals the day of reckoning when the bubble bursts. For investors with a long position in the stock market, a conservative strategy that might be advised is as follows: if the first three patterns emerge, and the HSI drops below the moving regression line (by which time the stock price would have dropped by more than 10% from its peak), then investors should sell their stocks to avoid market crashes, as well as a deep and long bear market.

This is consistent with the idea that nobody invests in a financial bubble after it has burst. Most investors should have sold their shares when the index dropped below the $-1$ SD trend line, by which time a market crash is highly likely, to be followed by a deep and long bear market. For aggressive investors, to generate the greatest wealth, they can adopt MA20 long and short strategies during bull runs, and MA20 short strategies after the stock price has dropped below the moving regression line from the peak, until the stock price breaks a dominant downward trend. As the analysis presented above shows, such strategies generate greater wealth than do *BH* strategies and simple *TA* strategies, which adopted long and short strategies for the entire period.

From the above, we conclude that *TA* analysis is not only useful in normal times, as shown in Wong *et al.* (2005), but *TA* strategies are also useful during the formation of bubbles and market crashes. This is not surprising as the market is regarded as highly inefficient when bubbles form, such that the stock price no longer depends on fundamentals. By applying technical indicators, investors can ride the trends to generate greater wealth during bubble formation and subsequent crashes.

It would be interesting to analyse credit bubbles and the properties of credit bubbles and stock market bubbles, which are very important, especially for regulators, in the sense that they can be used as early warning signals. It should be noted that our paper is a technical analysis paper. Technical analysis is different from fundamental analysis or complicated financial theory, in which there could be many variables, for which the corresponding data could be difficult to obtain. The former basically only relies on the information of price movements to obtain some profit generating rules, which laypersons could use when they have only price data. However, the latter could include more complicated variables and factors, such as credit bubbles and/or rational bubbles (for further details, see Hirano and Yanagawa, 2010; Farhi and Tirole, 2012).

As our paper is a technical analysis paper, we follow most, if not all, other technical analysis papers in that we rely only on the information contained in price movements. Our paper is intended to suggest some profit generating rules that are based only on the information contained in price movements. We will leave the research associated with credit bubbles and/or rational bubbles to a future study in fundamental analysis or new advanced financial theory that might be able to suggest variables beyond price movements alone.

We also note that there are two possibilities after a new rule is announced. One possibility is that the rule cannot be used to lead to profits after an announcement. This is because when some investors apply the rule and, say, find that stock A is underpriced and stock B is overpriced, then one will buy long stock A and sell short stock B. If many investors behave in the same manner, the price of stock A will rise and the price of stock B will fall, so that the “arbitrage opportunity” will disappear.

However, there is another possibility. For example, in our paper we suggest that the stock market is very likely to crash if all four properties appear in the market. If many investors accept our conjecture and adopt our proposed strategy, they will sell the stocks when the stock price drops below the $-1$ SD trend line. If many investors act in the same way, then even if it is a false signal of a bubble, the market will still crash as it will become a self-fulfilling prophecy that the stock will plummet, so that investors could still earn enormous profits. We are not sure whether our rule will be useful or become a self-fulfilling prophecy after announcement. This is an interesting direction of future research.

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