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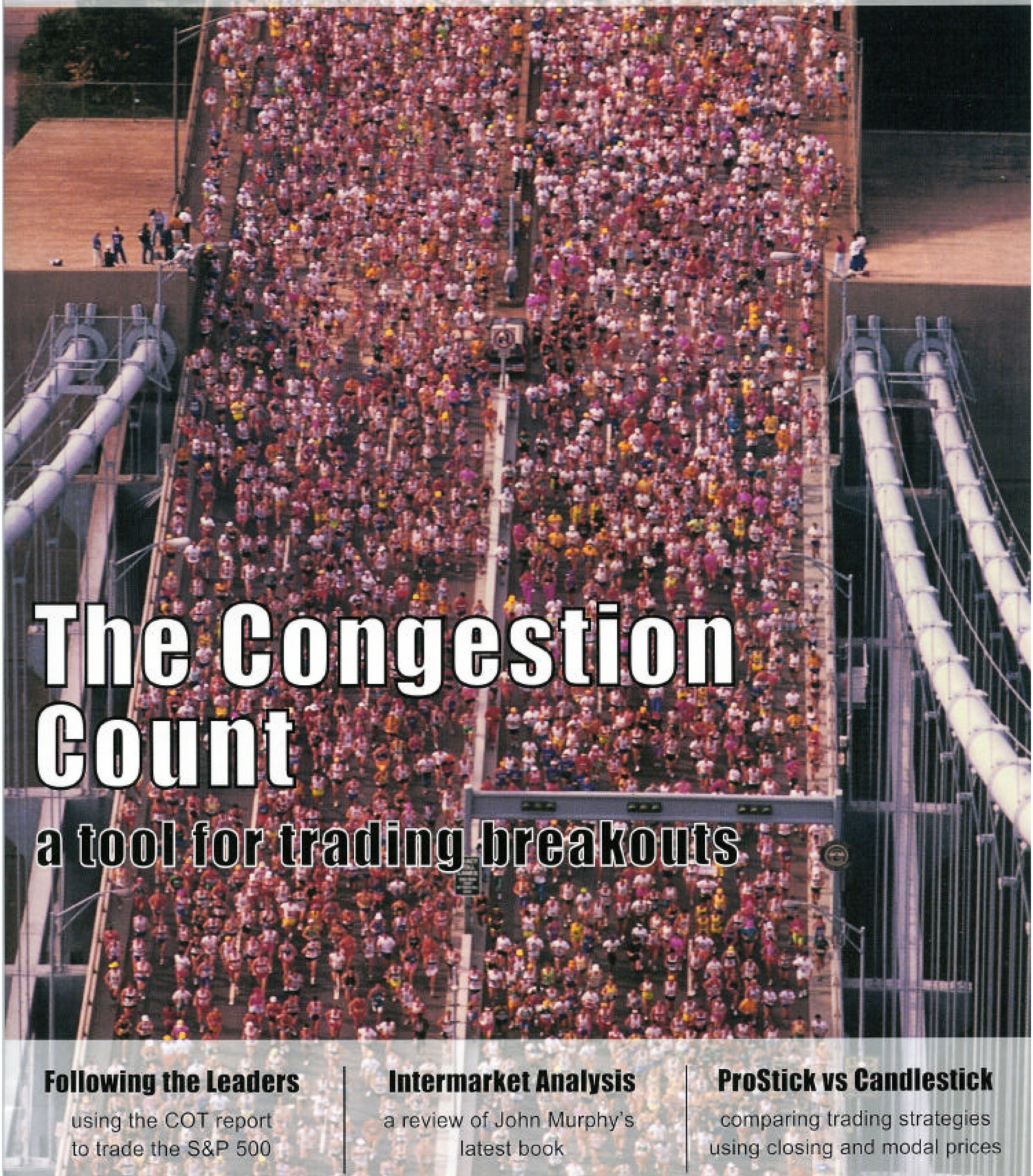

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Subject Matters

PROSTICK VS CANDLESTICK

A COMPARISON OF TRADING STRATEGIES USING MODAL POINT AND CLOSING PRICE DATA

by Quincy Chi-Fai Chan and Terence Tai-Leung Chong

Quincy Chan and Terence Chong use ProStick modal data to assess the performance of moving average and relative strength trading strategies. If trading rules based on modal point data were to perform better than those based on closing price data, then it may mean that previous research which had concluded against technical analysis (and in favour of the efficient market hypothesis) may need to be revisited.

Academic studies about technical trading rules are largely based on closing price data. In this article we introduce the ProStick, a new charting method that is based on the candlestick. The candlestick carries four pieces of market information: the opening, high, low, and closing prices (OHLC). A ProStick preserves the basic features of the candlestick, but also contains the active range (a price interval which contains about 70% of the transactions), the extreme tails (the top and bottom extreme prices which contain about 3% of the transactions) and the modal point (the daily heaviest trading price). For the purposes of comparison, a ProStick and a candlestick chart are shown in Figure 1.

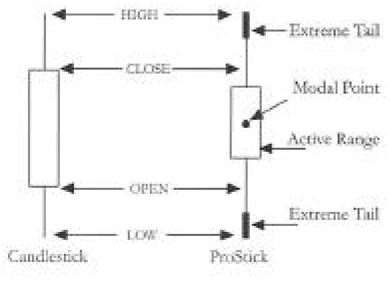

Figure 1. Candlestick and ProStick

The trading rules

We compare the performance of simple moving average (SMA) and relative strength index (RSI) trading strategies based on (ProStick) modal point and closing price data from the Hang Seng Index (see box).
SMA rules are widely studied (Lakonishok and LeBaron, 1992; LeBaron, 1998; Brock, Coutts and Cheung, 2000). The N-day SMA at time t is given by the following expression:

$$SMA_N(t) = \frac{1}{N} \sum_{i=t-N+1}^{t} P(i),$$

Where P(i) is the price of the index at time i and N is the window width of the moving average. To give an in-depth comparison of profitability, the 5-, 10-, 20-, 50-, 150-, 200- and 250-day MAs are investigated.
The trading signals at time t can be defined as follows:

$$\text{Buy}: P(t) \geq SMA_N(t) \text{ and } P(t-1) < SMA_N(t-1),$$

$$\text{Sell}: P(t) < SMA_N(t) \text{ and } P(t-1) > SMA_N(t-1).$$

Therefore, a buy signal at date t will be generated when the price crosses the moving average from below. Conversely, when the price penetrates the moving average from above, a sell signal is triggered.

We also study the profitability of RSI trading strategies (Wilder, 1978). The N-day RSI at time t is defined as:

$$RSI_N(t) = \frac{\sum_{i=0}^{N-1} |P(t-i) - P(t-i-1)| \, I\{P(t-i) > P(t-i-1)\}}{\sum_{i=0}^{N-1} |P(t-i) - P(t-i-1)|} \times 100$$

Where $|x|$ denotes the absolute value of x, $I\{\cdot\}$ is an indicator function which equals one when the statement inside the bracket is true and equals zero otherwise. N is the window width of the RSI. The smaller the value of N, the more sensitive the oscillator becomes and the higher its volatility will be. In this article, the 9-, 14-, 21- and 28-day RSIs are examined.

A stock or index is considered oversold if its RSI is below 30, whereas it is considered overbought if its RSI is above 70. A reading of 100 implies a non-decreasing price movement, whereas a reading of 0 implies a non-increasing price movement. A reading above 50 implies a bullish market whereas a reading below 50 implies a bearish market. The trad-

$$\text{Buy}: RSI_N(t) \geq 50 \text{ and } RSI_N(t-1) < 50,$$

$$\text{Sell}: RSI_N(t) < 50 \text{ and } RSI_N(t-1) > 50.$$

The data

Modal point data for the Hang Seng Index (HSI) from 30 June 1999 to 2 July 2002 is analysed. The sample size is 738 after holidays have been excluded. For comparison, the daily closing price of the HSI over the same period will also be examined. Table 1 reports the summary statistics for the daily returns approximated by the log first differences of the HSI using closing price and modal point.

30/6/1999-2/7/200 Statistic	daily returns of closing price	daily returns of modal point
T	738	738
Mean	-0.000345	-0.000362
Std. Dev	0.017180	0.016294
Skewness	-0.314235	-0.339460
Kurtosis	5.247818	4.969739

Table 1. Summary statistics for the log first differences of the HSI using closing price and modal point

From Table 1, it can be seen that the mean daily returns are slightly negative. The standard deviation of daily returns for closing price and modal point are 0.0172 and 0.0163 respectively. The skewness and kurtosis are also computed. The skewness figures in Table 1 coincide with the results in Hudson et al. (1996) and Mills (1997), who found skewness ranged from -0.43 to 0.31 in other stock markets. The kurtosis for daily returns is close to 5 in both data sets. As a result, the distribution of the HSI returns is somewhat leptokurtic, which agrees with the findings from other stock markets.

ing signal at time t can be defined as follows: Therefore, a buy signal at date t will be triggered when the RSI crosses 50 from below. Conversely, when the RSI penetrates 50 from above, a sell signal is generated.

The returns from the SMA and RSI rules are compared to the return from a buy-and-hold rule. For the simple buy-and-hold strategy, the HSI is purchased at the beginning of the period and sold at the end of the period. We use the closing prices for the calculation of the return (the result should not be materially different to that of using modal point) and the return from the simple buy-and-hold strategy is considered our benchmark return. Following Leung and Chong (2003), the performance of a trading rule is evaluated in terms of the annualized rate of return. Since there are about 250 trading days each year, the annualized rate of return is defined by:

$$R = [(1 + r_1)(1 + r_2)(1 + r_3)\dots(1 + r_m)]^{\frac{250}{T}} - 1,$$

Where m is the number of transactions in the sample; R is the annual rate of return; S(j) and B(j) are selling and buying prices

$$1 + r_j = \frac{S(j)}{B(j)};$$

respectively in the jth transaction; and T is the number of trading days in the sample. To better assess the profitability, the annual transaction costs are included. The annual rate of transaction cost is given by:

$$\text{Annual rate of transaction cost (ATC)} = m \times c \times$$

Where c is the percentage cost for each transaction. We employ $c = 0.25\%$ per complete transaction. After getting the annualized transaction cost, the annualized adjusted rate of return (AR) is defined as:

$$AR = R - ATC.$$

Results and conclusion

In this section, we study the investment returns in the case where short selling is allowed. Table 2 summarizes the results.

Comparing the two data sets, with the exception of SMA_{150}, returns are all positive. For the SMA rules with closing price data, the annual rate of unadjusted return is maximized at SMA_{10}, which is 38.95%. For modal point data, the highest return is also obtained by SMA_{10}. The return for SMA_{10} is 32.23%. Annual adjusted returns range from -2.94% to 24.19% for modal point and from -4.23% to 30.14% for closing price data. Comparing the profitability of applying SMA rules to two different data sets, with the exception of

HSI	m	R (%)	Correct	Error	ATC (%)	AR (%)
Closing Price						
SMA_{5}	179	28.96	68	111	15.16	13.80
SMA_{10}	104	38.95	38	66	8.81	30.14
SMA_{20}	74	23.37	20	54	6.27	17.11
SMA_{50}	50	9.60	15	35	4.23	5.37
SMA_{150}	28	-1.86	6	22	2.37	-4.23
SMA_{200}	16	8.17	5	11	1.36	6.81
SMA_{250}	16	3.71	2	14	1.36	2.36
RSI_{9}	95	-1.91	30	65	8.05	-9.95
RSI_{14}	77	24.66	31	46	6.52	18.14
RSI_{21}	57	12.93	21	36	4.83	8.11
RSI_{28}	49	9.25	19	30	4.15	5.10
Modal Point						
SMA_{5}	181	30.07	76	105	15.33	14.74
SMA_{10}	95	32.23	37	58	8.05	24.19
SMA_{20}	74	27.23	26	48	6.27	20.96
SMA_{50}	46	16.54	14	32	3.90	12.64
SMA_{150}	32	-0.23	11	21	2.71	-2.94
SMA_{200}	14	8.38	6	8	1.19	7.19
SMA_{250}	14	4.08	4	10	1.19	2.90
RSI_{9}	95	-6.78	28	67	8.05	-14.83
RSI_{14}	69	30.19	29	40	5.84	24.34
RSI_{21}	51	18.53	23	28	4.32	14.21
RSI_{28}	53	8.74	21	32	4.49	4.25
B & H	1	-8.26	0	1	0.09	-8.34

Table 2. Annual rate of return with short selling

"SMA RULES BASED ON MODAL POINT DATA OUTPERFORM SMA RULES BASED ON CLOSING PRICES."

SMA_{10}, modal point data generates a higher return. Evidently, SMA rules based on modal point data outperform SMA rules based on closing prices.

Table 2 also reports the annual adjusted return for SMA trading rules, taking into account transaction cost. The results based on closing price data suggest that the best window size is 10-days for the SMA trading rule. Returns are positive for all window sizes except SMA_{150}, which is -4.23% per year. The SMA trading rule clearly outperforms a simple buy-and-hold trading strategy.
For the RSI trading rule, using the closing price data, the unadjusted return is 24.67% per year for RSI_{14}. The return for RSI_9 is -1.91% per year. Note that the annual return generated by modal point data is higher than that generated by closing price data for RSI_{14} and RSI_{21}. The RSI_{14} based on modal point data generates a return of 30.19% per year.

However, closing price data outperforms modal point data for RSI_9 and RSI_{28}. Note that the RSI returns are all positive and higher than the buy-and-hold return in both data sets, with the exception of RSI_9.

In conclusion, this article introduces the concept of modal point into the research literature. We compare the profitability of certain trading rules based on closing price and modal point data. It is found that SMA and RSI rules outperform simple buy-and-hold tactics for both closing price and modal point data. Moreover, SMA rules based on modal point data generate higher returns than those based on closing price data, whereas the result is mixed under the RSI rule. Finally, SMA trading rules with a smaller window size tend to generate a higher annual return. Our findings suggest that using closing price data for SMA trading strategies may not be as profitable as using modal point data. This may also mean that previous studies which support the efficient market hypothesis may need to rewrite their results if model point data were to be used for the calculation of returns instead of closing price data. Given the important implication of our results, the extension of our analysis to other trading rules is worth further exploration.

Quincy Chi-Fai Chan, Bank of China, and Terence Tai-Leung Chong, Department of Economics, The Chinese University of Hong Kong

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