Tests for Two-Day Candlestick Patterns in the Emerging Equity Market of Taiwan

Tsung-Hsun Lu and Yung-Ming Shiu

ABSTRACT: Using the Taiwan 50 Index component stocks for the period from January 2, 2002, to December 31, 2009, this study examines the predictive power of candlestick trading strategies. A four-digit numbers approach is employed to categorize two-day candlestick patterns. We find that the Taiwanese stock market is not efficient. We also document that two candlestick bullish patterns consistently outperform others. The main contributions of this study include addressing a range of two-day candlestick patterns, finding existing patterns not profitable, and showing two new patterns as profitable.

KEY WORDS: candlesticks, technical analysis, two-day patterns.

According to the efficient market hypothesis, one cannot predict stock prices or their future trends because markets reflect all publicly available information rapidly and accurately. It should thus be impossible to earn abnormal returns with technical analysis (Fama 1970; Malkiel 1996). However, abundant evidence shows the existence of irrational behavior phenomena in financial markets. Kahneman and Tversky (1979) note the reflection effect, a heuristic-driven bias in prospect theory that reveals the irrationality of investors facing gains and losses. In addition, many studies have shown the existence of abnormal returns, including loss aversion (Benartzi and Thaler 1995), feedback (De Long et al. 1990), noisy rational expectations (Blume et al. 1994; Brown and Jennings 1989; Grundy and McNichols 1989; Hellwig 1982), disequilibrium (Beja and Goldman 1980), market power (Froot et al. 1992), instability (Goldbaum 2003), agent-based modeling (Schmidt 2002), and chaos theory (Clyde and Osler 1997).

Technical analysis is the study of past prices and related summary statistics for the purpose of predicting future price movements (Brock et al. 1992). It mainly includes two types, visual patterns in charts and mathematical indicators through calculations (Fock et al. 2005). Levy (1971) reviews thirty-two patterns of stock prices and examines the excess returns for New York Stock Exchange (NYSE) securities. He finds that charting analysis failed to generate abnormal returns. Sullivan et al. (1999) employ bootstrap reality check methodology to examine approximately 8,000 trading rules identified from five technical trading systems—filters, moving averages, support and resistance, channel breakouts, and on-balance volume averages—and ultimately claim that technical analysis is unable to deliver significant results. Brock et al. (1992) treat support and resistance levels as trading rules, and their results provide strong support for technical strategies. In addition, Park and Irwin (2007) demonstrate that among ninety-five modern studies of technical analysis, fifty-six reveal positive results, twenty show negative results, and nineteen obtain mixed results.

Tsung-Hsun Lu (corresponding author; r4895107@mail.ncku.edu.tw), is a Ph.D. candidate in the Department of Business Administration, National Cheng Kung University, No. 1, University Road, Tainan City 701, Taiwan (ROC). Yung-Ming Shiu (yungming@nccu.edu.tw) is a professor in the Department of Risk Management and Insurance, National Chengchi University, Taipei, Taiwan.

Emerging Markets Finance & Trade / January–February 2012, Vol. 48, Supplement 1, pp. 41–57.

1540-496X/2012 $9.50 + 0.00.
DOI 10.2753/REE1540-496X4801S104

Technical trading rules are probably profitable in emerging markets. McKenzie (2007) tests three technical trading rules, the variable-length moving average, fixed-length moving average, and trade range breakout, for seventeen countries over the period of January 1986 to September 2003. Krausz et al. (2009) use nine Pacific Basin stock market indexes to investigate the link between the nonlinear dynamics of stock returns and technical trading rules. Finally, they claim that technical analysis is useful in emerging markets.

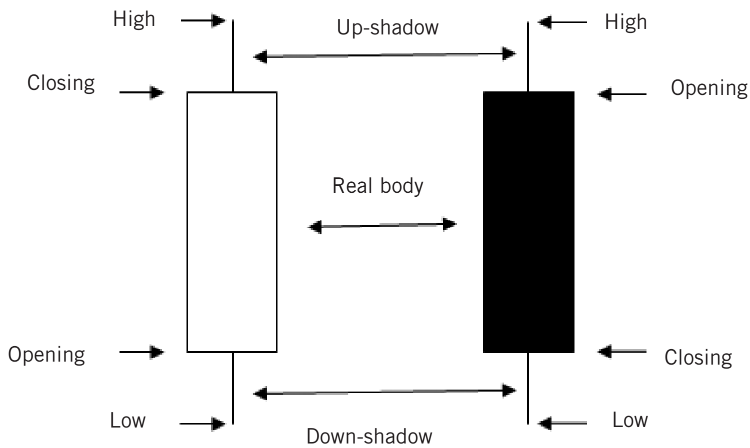
The paper by Caginalp and Laurent (1998) is one of the first empirical studies on candlesticks. They use a z-test to examine eight three-day reversal patterns for all S&P 500 stocks over the period 1992–96, and claim that candlestick analysis has predictive value. In addition, Goo et al. (2007) utilize the daily data of twenty-five component stocks in the Taiwan Top 50 Tracker Fund and Taiwan Mid-Cap 100 Tracker Fund over the period from 1997 to 2006, and find strong support for candlestick techniques. Meanwhile, they suggest that the performance of candlesticks can be further improved by implementing stop-loss strategies. Furthermore, Shiu and Lu (2011) use quantile regression to examine three confirmation factors of candlestick charting for all electronic securities in the Taiwan Stock Exchange between 1998 and 2007, and find that the second day's opening price and the real body sizes affect candlestick efficacy.

On the contrary, Fock et al. (2005) were the first to employ five-minute data from the index futures on the German stock index and the bond futures on German government bonds to test candlesticks against a benchmark built from randomization, but their empirical results are poor. Other studies employ bootstrap methodology. For instance, Marshall et al. (2006) investigate thirty-five stocks on the Dow Jones Industrial Average over the period 1992–2001, and find that candlestick technical analysis has no value. Marshall et al. (2008) use the same method to study the Japanese stock market, and their results are also disappointing for candlestick trading strategies. Similarly, Horton (2009) utilizes three nonparametric tests, the Kolmogorov–Smirnov test, the Cramer–von Mises test, and the Birnbaum–Hall test, to analyze nine patterns of candlesticks for 349 stocks in the S&P 500 index, and finds support for the efficient market hypothesis, but not for candlestick technical analysis.

Some papers in these fields, however, have been misguided because of an inadequate understanding of candlesticks. Central to this issue is the problem of recognition of patterns. However, much attention has been paid to the six two-day reversal patterns mentioned in Nison (1991), but the remaining two-day patterns have been relatively neglected in the literature. We thus attempt to investigate some patterns not previously considered, even by experienced charting analysts. Our intention is to consider all patterns formed by two candlestick single lines, not only those in Nison's book. One of the possible contributions of our study is that we devise a four-digit numbers approach to categorize two-day candlestick patterns in a scientific way. There are twenty-four types in total.

The work that we present in this paper is an attempt to supplement the findings of earlier studies, and it is similar to the previous research discussed above, in that the focus is on the predictive power of candlesticks. A key difference between this paper and prior studies on candlesticks, however, is that we examine two-day candlestick patterns using a large-scale and systematic approach. In addition, we utilize several statistical tests and methods to ensure the correctness of our results. After rigorous procedures, we find that bullish pattern 1234 in downtrend markets and bullish pattern 1324 in uptrend markets could help investors profit in the Taiwan stock market. This research is still in its infancy, but it may contribute to unraveling the mystery of candlesticks. We believe that our results could enable investors to employ two-day candlestick patterns more effectively.

Figure 1. Single candlestick construction



This paper is closely related to those of Goo et al. (2007) and Shiu and Lu (2011). They also use daily data on Taiwan individual stocks. Goo et al. (2007) utilize stop-loss strategies with candlesticks to obtain better performance, and find that the Bullish Harami pattern possesses genuine forecasting power. Shiu and Lu (2011) address three key factors to strengthen the efficacy of six two-day candlestick patterns, and suggest that the Bearish Harami pattern seems to be good for investors. We, however, use a systematic method to document a range of new two-day candlestick patterns. We also find that existing patterns in practitioner books or tested by earlier studies are not profitable. Our results show that some new patterns are indeed profitable.

Candlestick Charting and Research Design

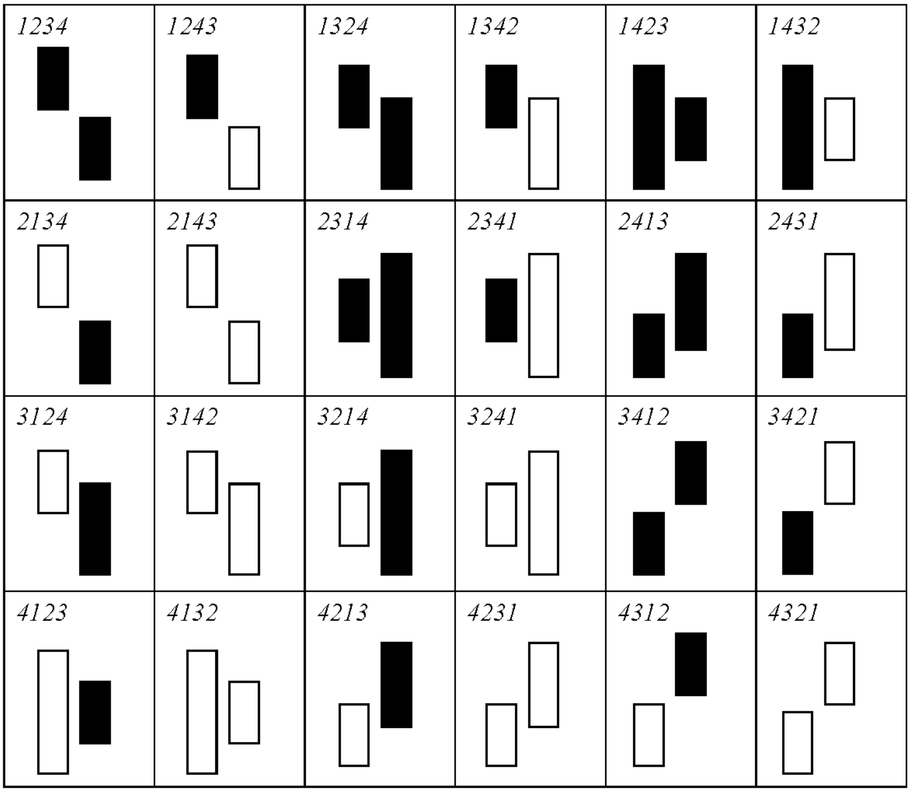
Candlestick charting is based on the recognition of visual patterns and was developed in Japan 400 years ago by Munehisa Honma, a wealthy rice farmer and commodity trader (Caginalp and Laurent 1998; Nison 1991). A few centuries later, Steve Nison introduced it to the Western world, where it has become increasingly popular (Nison 1991).

Candlestick charting is a basic tool of technical analysis, and is available in many software and charting packages, including Microsoft Excel. This technique transfers investor emotions into charts, creates patterns based on changes in investor sentiment, and can reflect the fear and greed of investors.

The information of four prices, that is, opening, high, low, and closing prices, can be used to construct a candlestick single line. The distance between the opening and closing prices is called the "real body" of the candlestick, colored white if the closing surpasses the opening and colored black if the reverse is true. If the high price is more than the real body, and the interval is represented by a line segment, it is called an "up-shadow." When the reverse is true, under the candlestick's real body is a "down-shadow" (Nison 1991) (shown in Figure 1).

We classify all two-day candlestick patterns using four-digit numbers. The ranks (N1 through N4) are converted into a pattern identification number by the equation $(N1 \times 1{,}000) + (N2 \times 100) + (N3 \times 10) + N4$, and therein N1 and N2 represent the

Figure 2. Categories for two-day candlestick patterns



opening and closing prices of the first day of the two-day pattern, respectively. In the same way, N3 and N4 represent the opening and closing prices of the second day of the two-day pattern, respectively (shown above left in the grids in Figure 2). The four-digit placeholders are numbered by their measurement of the four prices in sequence. To take a simple example, "pattern 1324" indicates that the first day's opening is higher than its closing, and the second day opens higher than the first day's closing but less than opening, and the second day closes lower than the first day's closing. This rule was designed to explore the identification and classification of all two-day patterns of candlesticks in a thorough, systematic, and scientific manner.

Candlestick patterns should always consider what happened before (Nison 1991). Our next step is, therefore, to identify uptrend and downtrend episodes prior to the patterns. Inspired by Caginalp and Laurent (1998) and Shiu and Lu (2011), we employ the five-day moving average, and on day t this is defined by:

$$MA_5 = \frac{C(t-4)+C(t-3)+C(t-2)+C(t-1)+C(t)}{5},$$

where $C(t)$ is the closing price on day t.

An uptrend on day t is defined by:

$$MA(t-6) < MA_5(t-5) < \ldots < MA_5(t-1) < MA_5(t).$$

In contrast, a downtrend on day t is defined by:

$$MA(t-6) > MA_5(t-5) > \ldots > MA_5(t-1) > MA_5(t).$$

Next, we define how to measure the returns generated by the two-day candlestick patterns. In this paper, we measure returns based on the following three rules. First, the start of the measuring is at the opening price on the day following a two-day pattern. Second, the end of the measuring is at the closing price on the first, fifth, and tenth holding day. Assume that the two-day pattern is formulated on day t. The equation for n-day returns is as follows:

$$\frac{Selling\ price_{t+n} - Buying\ price_{t+1}}{Buying\ price_{t+1}} \times 100\%,$$

where the $Selling\ price_{t+n}$ represents the closing price on day $t + n$ and the $Buying\ price_{t+1}$ denotes the opening price on day $t + 1$.

Note that returns are calculated on a buy-and-hold basis. In other words, positive return rates for bullish signals indicate that the patterns correctly predict the direction of price movements, and so do the negative return rates for bearish signals. Third, as in Brock et al. (1992) and Marshall et al. (2006), we examine the profits by raw returns rather than abnormal returns.

Moreover, in the Taiwan stock market, transaction costs include trading taxes, brokerage commissions and fees, and depository fees when a margin transaction occurs. Trading taxes generally are 0.3 percent, and brokerage commissions and fees are 0.285 percent for a round-trip trade. Due to the prevalence of electronic trading in recent years, brokerage commissions and fees have fallen by at least 50 percent. Meanwhile, some of the risk resulting from trading itself is regarded as a potential cost. The risk of bid-ask spreads, which are generally unobservable, consists of execution costs, liquidity costs, and slippage costs. In this paper, the aforementioned costs are arbitrarily set at 1 percent for a round-trip trade.

Data and Empirical Results

Our data consist of fifty stocks from the Taiwan 50 Index for the period from January 2, 2002, to December 31, 2009. This particular sample set was chosen merely to provide a good mix of industries and representative firms. Among the fifty stocks, twelve stocks failed to exist for the whole period. They were not yet included in the Taiwan 50 Index on January 2, 2002. For the representation of the Taiwan stock market, we cannot exclude these twelve stocks, and we trace back to their respective listing dates.

First of all, we examine the profitability of all twenty-four patterns to test their predictive power. Whereas the return series exhibits skewness,[1] we use the skewness-adjusted t-statistic developed by Johnson (1978) to test the null hypothesis that average returns generated from candlestick trading rules are zero. The skewness-adjusted t-statistic is defined by:

$$T_{sa} = \sqrt{n}\left(s + \frac{\varphi \times s^2}{3} + \frac{\varphi}{6n}\right),$$

where

$$s = \frac{\bar{R}_t}{\sigma(R_t)}, \quad \varphi = \frac{\sum_{i=1}^{n}(R_{it} - \bar{R}_t)^3}{n\sigma(R_t)^3}.$$

Because the distribution of stock returns may not follow a normal distribution, Lukac and Brorsen (1990) suggest that nonparametric statistics are more appropriate than parametric statistics. As stated in Conover (1999), the binomial test has remarkable versatility, and it is suitable to test almost any data hypothesis. Conover notes: "Even in situations where more powerful tests are available, the binomial test is sometimes preferred because it is usually simple to perform, simple to explain, and sometimes powerful enough to reject the null hypothesis when it should be rejected" (1999, p. 124). We thus employ the binomial test to examine the randomization of two-day patterns of candlesticks. The data are examined with both the skewness-adjusted *t*-test and binomial test to find the trading rules that have genuine predictive power. The null hypothesis of the skewness-adjusted *t*-test is H_0: $\mu = 0$ for the average returns, and with the null hypothesis of the binomial-test, it is H_0: $p = 0.5$ for the hit-ratios.

Table 1 summarizes the results for all the samples without distinguishing market episodes. A total of 54,955 patterns are detected, and pattern 4321 appears most frequently, at 8,244 times. The results that satisfy both the skewness *t*-test and the binomial test are regarded as significant results. Note that a positive value for the bullish signal and a negative one for the bearish signal reveal that the pattern correctly predicted the direction of the market. However, after adjusting by transaction costs of 1 percent per trade, all patterns for one, five, and ten holding days failed to deliver positive returns. According to the basic principle of candlestick charting, no pattern has value until the prior trend has finished. Therefore, we immediately test the predictive power of candlesticks by distinguishing market episodes, uptrend episodes, and downtrend episodes, in the following section.

Check for Robustness

Subsamples Based on Previous Trends

We identify three distinct types of market trends (uptrend, downtrend, and flat markets) before the patterns appear by the rules mentioned above. As shown in Table 2, in an uptrend market, bullish pattern 1324 and bearish pattern 4231 show significant results for five holding days, and bullish patterns 1234, 1243, and 1324 exhibit significant results for ten holding days. Simultaneously, in an uptrend market, only bullish pattern 1324 has powerful predictability. It has returns of 1.18 percent and 1.20 percent when holding for five and ten days, respectively.

Table 3 shows that in a downtrend market, bullish pattern 1234 demonstrates outstanding performance. We find significant results on both five and ten holding days after transaction costs. In addition, the hit-ratio of this pattern is over 58 percent. All these findings indicate that pattern 1234 is a bullish reversal pattern to execute a buying strategy. The results indicating that the market forces finally become exhausted are consistent with prior studies finding that stocks that experience a price rise or fall often have a significant reversal (Jegadeesh 1990; Lehmann 1990).

All these findings make it clear that it is necessary to distinguish trends before patterns, and that patterns 1324 and 1234 both have significant practical implications. To put

Table 1. Numbers and returns of patterns

		1-day		5-day		10-day	
Patterns	**No.**	**Returns (%)**	**Hit-ratio (%)**	**Returns (%)**	**Hit-ratio (%)**	**Returns (%)**	**Hit-ratio (%)**
1234	7,255	0.18 (< 0 .01)*	56.12 (< 0.01)*	0.62 (< 0.01)*	53.81 (< 0.01)*	0.80(< 0.01)*	54.60 (< 0.01)*
1243	2,479	–0.14 (< 0.01)*	50.36 (< 0.01)*	0.10 (< 0.01)*	53.65 (< 0.01)*	0.32(0.08)	52.20 (0.70)
1324	3,959	0.04 (0.29)	52.42 (< 0.01)*	0.45 (< 0.01)*	50.24 (0.77)	0.51 (< 0.01)*	51.68 (0.67)
1342 (Piercing)	2,098	–0.16 (<0.01)*	49.31 (< 0.01)*	0.08 (0.46)	50.48 (0.68)	0.29 (0.13)	51.58 (0.68)
1423	1,410	0.13 (0.03)*	54.49 (0.12)	0.35 (0.11)	49.57 (0.77)	0.03 (0.89)	51.00 (0.59)
1432 (Bullish Harami)	2,408	–0.09 (0.06)	49.75 (< 0.01)*	0.22 (0.03) *	48.21 (0.08)	0.44 (0.01)*	50.62 (0.28)
2134	1,549	–0.11 (0.08)	52.23 (< 0.01)*	–0.09 (0.21)	50.42 (0.76)	0.26 (0.25)	52.16 (0.88)
2143	562	–0.17 (0.08)	50.89 (< 0.01)*	–0.36 (0.25)	51.42 (0.53)	–0.41 (0.23)	47.32 (0.02)*
2314	1,326	–0.21 (< 0.01)*	50.34 (< 0.01)*	0.40 (0.23)	48.27 (0.22)	0.38 (0.11)	50.76 (0.48)
2341 (Bullish Engulfing)	1,420	–0.30 (< 0.01)*	46.42 (< 0.01)*	–0.47 (0.24)	46.69 (0.01)*	–0.22 (0.33)	49.54 (0.06)
2413	557	–0.06 (0.50)	51.53 (0.01)*	0.16 (0.85)	48.29 (0.45)	–0.45 (0.25)	46.94 (0.05)
2431	2,801	–0.13 (< 0.01)*	47.53 (< 0.01)*	–0.27 (0.09)	45.13 (< 0.01)*	–0.21 (0.16)	48.25 (< 0.01)*
3124	1,672	–0.01 (0.87)	54.43 (< 0.01)*	0.52 (< 0.01)*	51.26 (0.32)	0.83 (< 0.01)*	54.85 (0.01)*
3142	320	–0.34 (< 0.01)*	48.61 (< 0.01)*	–0.62 (0.47)	43.75 (0.03)*	–0.28 (0.53)	50.77 (1.00)

(continues)

Table 1. Continued

		1-day		5-day		10-day	
Patterns	**No.**	**Returns (%)**	**Hit-ratio (%)**	**Returns (%)**	**Hit-ratio (%)**	**Returns (%)**	**Hit-ratio (%)**
3214 (Bearish Engulfing)	2,543	–0.03 (0.56)	52.56 (< 0.01)*	0.60 (< 0.01)*	50.69 (0.50)	0.80 (< 0.01)*	53.00 (0.21)
3241	590	–0.36 (< 0.01)*	44.22 (< 0.01)*	–0.51 (0.01)*	44.58 (0.01)*	–0.52 (0.16)	46.57 (0.02)*
3412	778	–0.26 (< 0.01)*	43.99 (< 0.01)*	–0.36 (< 0.01)*	42.03 (< 0.01)*	–0.58 (0.03)*	47.94 (0.06)
3421	2,640	–0.22 (< 0.01)*	46.82 (< 0.01)*	–0.04 (0.20)	45.11 (< 0.01)*	–0.12 (0.45)	48.25 (< 0.01)*
4123 (Bearish Harami)	1,579	–0.13 (0.02)*	50.38 (< 0.01)*	–0.47 (0.17)	47.37 (0.04)*	–0.24 (0.26)	48.68 (0.01)*
4132	654	–0.05 (0.59)	54.24 (< 0.01)*	–0.51 (0.33)	46.64 (0.09)	–0.35 (0.28)	49.85 (0.26)
4213 (Dark Cloud Cover)	3,368	–0.05 (0.22)	49.52 (< 0.01)*	0.07 (0.34)	47.21 (< 0.01)*	0.04 (0.79)	49.23 (< 0.01)*
4231	1,720	–0.16 (< 0.01)*	50.20 (< 0.01)*	–0.61 (0.05)*	47.56 (0.05)*	–0.34 (0.08)	50.06 (0.05)
4312	3,023	–0.08 (0.05)	48.24 (< 0.01)*	–0.31 (< 0.01)*	42.77 (< 0.01)*	–0.28 (0.06)	48.25 (< 0.01)*
4321	8,244	–0.26 (< 0.01)*	45.83 (< 0.01)*	–0.24 (< 0.01)*	44.52 (< 0.01)	–0.06 (0.50)	49.23 (0.21)

Notes: The names given in parentheses in the first column can be found in Nison (1991). Hit-ratios represent the proportion of positions with positive returns. * statistically significant at the 5 percent level.

Table 2. Results in uptrend markets

		1–day		5–day		10–day	
Patterns	**No.**	**Returns (%)**	**Hit–ratio (%)**	**Returns (%)**	**Hit–ratio (%)**	**Returns (%)**	**Hit–ratio (%)**
1234	1,028	0.33 (< 0.01)*	60.42 (0.05)	0.93 (< 0.01)*	55.16 (< 0.01)*	1.34 (< 0.01)*	55.19 (0.02)*
1243	347	0.04 (0.72)	51.16 (0.01)*	0.54 (0.08)	51.59 (0.59)	1.38 (< 0.01)*	57.75 (0.01)*
1324	564	0.02 (0.83)	50.30 (0.03)*	1.18 (< 0.01)*	54.43 (0.04)*	1.20 (< 0.01)*	53.74 (0.04)*
1342 (Piercing)	318	–0.07 (0.55)	50.65 (0.01)*	0.45 (0.24)	50.94 (0.78)	1.39 (< 0.01)*	55.63 (0.10)
1423	199	–0.25 (0.05)	45.89 (< 0.01)*	0.06 (0.89)	47.74 (0.57)	0.66 (0.14)	53.26 (0.86)
1432 (Bullish Harami)	358	–0.11 (0.25)	48.87 (< 0.01)*	0.53 (0.09)	48.32 (0.56)	1.48 (< 0.01)	53.12 (0.70)
2134	182	–0.21 (0.14)	49.12 (0.02)*	0.26 (0.54)	53.85 (0.34)	0.35 (0.52)	48.39 (0.47)
2143	67	–0.21 (0.36)	51.92 (0.49)	0.13 (0.36)	52.24 (0.81)	–0.50 (0.51)	43.27 (0.06)
2314	161	–0.41 (< 0.01)*	43.07 (< 0.01)*	0.33 (0.88)	48.45 (0.75)	1.02 (0.05)	54.31 (0.46)
2341 (Bullish Engulfing)	198	–0.74 (< 0.01)*	39.41 (< 0.01)*	–0.81 (0.01)*	37.37 (< 0.01)*	–0.33 (0.49)	46.64 (0.14)
2413	52	–0.20 (0.30)	45.35 (0.11)	–1.23 (0.14)	40.38 (0.21)	–0.13 (0.88)	46.51 (0.45)
2431	351	–0.23 (0.02)*	45.76 (< 0.01)*	0.10 (0.86)	43.59 (0.02)*	0.00 (1.00)	50.00 (0.16)
3124	215	0.25 (0.04)*	56.18 (0.56)	1.62 (< 0.01)*	55.81 (0.10)	1.76 (< 0.01)*	55.06 (0.19)
3142	40	0.07 (0.78)	58.46 (0.80)	–0.11 (0.40)	45.00 (0.64)	–1.88 (0.06)	38.46 (0.08)

(continues)

Table 2. Continued

Patterns	No.	1–day Returns (%)	1–day Hit–ratio (%)	5–day Returns (%)	5–day Hit–ratio (%)	10–day Returns (%)	10–day Hit–ratio (%)
3214 (Bearish Engulfing)	359	–0.13 (0.24)	50.66 (0.01)*	1.13 (< 0.01)*	52.09 (0.46)	1.60 (< 0.01)	53.90 (0.38)
3241	76	–0.34 (0.11)	44.83 (< 0.01)*	–0.54 (0.26)	43.24 (0.30)	–0.33 (0.70)	47.41 (0.40)
3412	71	–0.59 (< 0.01)*	40.52 (< 0.01)*	0.17 (0.19)	36.62 (0.03)*	–0.04 (0.95)	47.37 (0.31)
3421	275	–0.29 (0.01)*	46.61 (< 0.01)*	–0.42 (0.06)	41.82 (< 0.01)*	0.61 (0.14)	51.25 (0.60)
4123 (Bearish Harami)	181	–0.26 (0.03)*	46.94 (< 0.01)*	–0.97 (0.01)*	40.88 (0.02)*	0.45 (0.30)	48.98 (0.18)
4132	74	–0.10 (0.70)	50.00 (0.05)*	–0.42 (0.59)	44.59 (0.40)	–0.26 (0.76)	49.09 (0.78)
4213 (Dark Cloud Cover)	397	–0.14 (0.11)	48.11 (< 0.01)*	–0.26 (0.18)	45.84 (0.11)	0.72 (0.03)*	51.35 (0.58)
4231	205	–0.28 (0.03)*	47.62 (0.02)*	–1.01 (< 0.01)*	38.05 (< 0.01)*	–0.15 (0.72)	51.36 (0.77)
4312	298	–0.29 (0.01)*	43.75 (< 0.01)*	–0.19 (0.18)	40.94 (< 0.01)*	–0.17 (0.67)	46.46 (0.05)*
4321	944	–0.34 (< 0.01)*	46.00 (< 0.01)*	–0.51 (< 0.01)*	39.72 (< 0.01)*	0.70 (< 0.01)*	51.67 (0.94)

Notes: The names given in parentheses in the first column can be found in Nison (1991). Hit-ratios represent the proportion of positions with positive returns. * statistically significant at the 5 percent level.

Table 3. Results in downtrend markets

		1-day		5-day		10-day	
Patterns	**No.**	**Returns (%)**	**Hit-ratio (%)**	**Returns (%)**	**Hit-ratio (%)**	**Returns (%)**	**Hit-ratio (%)**
1234	793	0.49 (< 0.01)*	60.09 (0.36)	1.23 (< 0.01)*	58.51 (< 0.01)*	1.61 (< 0.01)*	58.56 (< 0.01)*
1243	307	–0.07 (0.61)	51.18 (< 0.01)*	0.66 (0.06)	55.70 (0.05)	0.07 (0.87)	53.66 (0.31)
1324	417	0.20 (0.04)*	55.05 (0.45)	0.15 (0.59)	51.08 (0.70)	0.42 (0.22)	50.63 (0.55)
1342 (Piercing)	254	–0.12 (0.35)	50.42 (< 0.01)*	0.89 (0.07)	53.54 (0.29)	0.24 (0.63)	52.79 (0.64)
1423	136	0.09 (0.57)	54.43 (0.19)	–0.11 (0.70)	50.00 (1.00)	–1.03 (0.05)	43.46 (0.01)*
1432 (Bullish Harami)	293	–0.22 (0.06)	48.52 (< 0.01)*	0.25 (0.31)	49.15 (0.82)	–0.24 (0.52)	49.89 (0.63)
2134	176	0.20 (0.21)	54.01 (0.34)	0.52 (0.13)	53.98 (0.33)	1.04 (0.04)*	58.19 (0.10)
2143	47	0.05 (0.85)	56.10 (0.74)	–0.20 (0.83)	51.06 (1.00)	–1.91 (0.04)*	40.24 (0.06)
2314	150	0.15 (0.37)	58.19 (0.95)	0.57 (0.59)	48.67 (0.81)	0.32 (0.60)	50.43 (0.74)
2341 (Bullish Engulfing)	165	–0.06 (0.67)	54.09 (0.03)*	0.20 (0.93)	47.27 (0.53)	–0.12 (0.85)	48.93 (0.34)
2413	69	–0.23 (0.29)	54.72 (0.50)	0.83 (0.55)	52.17 (0.81)	0.35 (0.69)	51.89 (0.92)
2431	357	–0.12 (0.21)	46.90 (< 0.01)*	–0.97 (0.38)	45.10 (0.07)	–1.30 (< 0.01)*	45.39 (< 0.01)*
3124	230	–0.06 (0.69)	54.29 (0.11)	0.00 (0.52)	48.26 (0.64)	0.52 (0.31)	53.68 (0.47)
3142	31	–0.55 (0.11)	40.43 (0.14)	–1.06 (0.97)	51.61 (1.00)	1.93 (0.09)	55.32 (0.56)

(continues)

Table 3. Continued

Patterns	No.	1-day Returns (%)	1-day Hit-ratio (%)	5-day Returns (%)	5-day Hit-ratio (%)	10-day Returns (%)	10-day Hit-ratio (%)
3214 (Bearish Engulfing)	291	0.18 (0.11)	54.77 (0.40)	0.46 (0.18)	53.61 (0.24)	0.20 (0.64)	52.99 (0.64)
3241	62	–0.42 (0.09)	44.34 (< 0.01)*	–0.27 (0.82)	46.77 (0.70)	–0.06 (0.95)	51.89 (1.00)
3412	107	–0.19 (0.31)	44.00 (0.02)*	–0.06 (0.32)	44.86 (0.33)	–0.95 (0.11)	48.00 (0.50)
3421	355	–0.34 (< 0.01)*	44.28 (< 0.01)*	–0.08 (0.72)	48.73 (0.67)	–0.85 (0.01)*	47.18 (0.03)*
4123 (Bearish Harami)	250	–0.05 (0.71)	51.20 (< 0.01)*	–0.31 (0.85)	50.40 (0.95)	–0.60 (0.21)	51.81 (0.87)
4132	92	0.22 (0.31)	60.77 (0.54)	–0.51 (0.94)	47.83 (0.75)	–0.89 (0.29)	50.00 (0.79)
4213 (Dark Cloud Cover)	452	0.05 (0.55)	50.87 (< 0.01)	0.40 (0.05)	50.66 (0.81)	–0.38 (0.23)	49.27 (0.08)
4231	234	0.00 (1.00)	53.68 (0.12)	–0.73 (0.71)	48.29 (0.65)	–0.79 (0.09)	46.72 (0.05)*
4312	430	–0.07 (0.47)	47.87 (< 0.01)*	–0.61 (0.02)*	43.26 (< 0.01)*	–0.83 (0.01)*	45.94 (< 0.01)*
4321	1,103	–0.27 (< 0.01)*	46.17 (< 0.01)*	–0.52 (0.73)	46.15 (0.01)*	–0.49 (0.02)*	48.51 (0.01)*

Notes: The names given in parentheses in the first column can be found in Nison (1991). Hit-ratios represent the proportion of positions with positive returns. * statistically significant at the 5 percent level.

it more clearly, the positive returns produced by pattern 1324 after an uptrend indicate that the bullish trend is continuing but the trend permits a significant fluctuation, a two-day drop. It is regarded as a bullish continuation pattern, and it hints that the upward trend does not end. The rationale is that originally the opening price of the first day is above the prior day's high, and thus the market abounds with an optimistic atmosphere, although the end of the market closes at a low price. Next, the second day of the pattern also sees the same process, opening high but closing low. In such a scenario, the bulls could easily overwhelm odd lotters who lose confidence in the bull market, and thus the former have more control over the market. This pattern is often called *flag consolidation* in practice.

As to pattern 1234, it can be regarded as the last struggle of the bears before they become a spent force. The second day's closing price makes a new low in the past few days, and the bears' power has then been completely exhausted. This pattern is also called a *stalled pattern* in practice. Pattern 1234 is appropriate for a buying signal after a downtrend because the bears' strength has been exhausted. These findings are consistent with prior studies, such as Brock et al. (1992) and Lai et al. (2010), showing that buying signals generally produce higher average returns than selling signals.

Let us compare and contrast our results with the six two-day patterns introduced in Nison's book. The Bearish Engulfing (pattern 3214 in uptrend markets) is frequently touted as the best strategy for short-selling, while the Bullish Engulfing (pattern 2341 in downtrend markets) is a well-known rush-buying strategy. In this paper, however, they both fail to show significant forecasting power. The remaining four patterns, the Bearish Harami (pattern 4123 in uptrend markets), the Dark Cloud Cover (pattern 4213 in uptrend markets), the Piercing (pattern 1342 in downtrend markets), and the Bullish Harami (pattern 1432 in downtrend markets) are all unprofitable after transaction costs.

To check the robustness of the results of patterns 1234 and 1324, we simulate these two patterns by three different trend situations, a five-day moving average over ten days and a ten-day moving average over ten and twenty days. Table 4 shows that pattern 1324 in uptrend market generates returns of 2.29 percent and 3.50 percent when holding for five and ten days, respectively, in a five-day moving average over ten days. Generally speaking, both patterns give convincing empirical results. It is worth noting that there are two appearances in Table 4. First, holding days enhance the returns. The ten-day average returns are higher than the five-day returns. Second, the significances weaken for the binomial test of pattern 1324 by a ten-day moving average over ten and twenty days. This confirms the suggestion by Nison (1991) and Morris (1995) that candlestick trading rules are most useful for short-term trading and suitable for horizons of approximately ten days.

We also calculate relative returns measured by absolute returns of stocks minus index returns for the profitable patterns to investigate the effect of candlesticks in Table 4. With only one exception of pattern 1234 for five holding days by a five-day moving average over ten days, all results in Table 4 seem to be influenced by index returns. Nevertheless, all absolute returns yielded by candlesticks can beat the market.

Nonparametric Test

The parametric *t*-test is sensitive to differences between two means, but the Kolmogorov–Smirnov test and the Birnbaum–Hall test are consistent against all types of differences between two distributions (Conover 1980: 368). Thus, we test the accurate signals from two

Table 4. Robust check results for patterns 1324 and 1234

	5-day				10-day			
	Absolute returns		Relative returns		Absolute returns		Relative returns	
Bullish patterns	**Returns (%)**	**Hit-ratio (%)**	**Returns (%)**	**Hit-ratio (%)**	**Returns (%)**	**Hit-ratio (%)**	**Returns (%)**	**Hit-ratio (%)**
1324 in uptrends								
MA5 over 10 days	2.29 (< 0.01*)	64.88 (< 0.01*)	1.78 (< 0.01*)	58.33 (0.07)	3.50 (< 0.01*)	62.40 (< 0.01*)	2.80 (< 0.01*)	54.55 (0.34)
MA10 over 10 days	1.34 (< 0.01*)	57.65 (< 0.01*)	0.95 (< 0.01*)	55.03 (0.02*)	2.11 (< 0.01*)	56.05 (0.03*)	1.37 (< 0.01*)	52.90 (0.23)
MA10 over 20 days	1.41 (0.01*)	53.33 (0.10)	0.86 (0.02*)	54.22 (0.35)	2.09 (0.01*)	53.94 (0.76)	1.41 (0.02*)	52.41 (0.70)
1234 in downtrends								
MA5 over 10 days	1.55 (< 0.01*)	58.76 (< 0.01*)	1.58 (< 0.01*)	58.96 (< 0.01*)	2.97 (< 0.01*)	62.87 (< 0.01*)	2.20 (< 0.01*)	63.19 (< 0.01*)
MA10 over 10 days	1.40 (< 0.01*)	60.59 (< 0.01*)	1.04 (< 0.01*)	58.02 (< 0.01)	1.57 (< 0.01*)	59.35 (< 0.01*)	1.18 (< 0.01*)	56.49 (< 0.01*)
MA10 over 20 days	1.11 (0.02*)	59.77 (< 0.01*)	1.05 (< 0.01*)	60.54 (< 0.01*)	2.22 (< 0.01*)	61.30 (< 0.01*)	1.78 (< 0.01*)	58.24 (0.01*)

Notes: The relative returns are measured by absolute returns of stocks minus index returns. * indicates statistical significance at the 5 percent level.

Table 5. Results for the Kolmogorov–Smirnov test and the Birnbaum–Hall test

Distributions tested	Kolmogorov–Smirnov	Birnbaum–Hall
Pattern 1234		
Uptrends vs. downtrends	0.0625*	
Downtrends vs. flats	0.0553*	
Flats vs. uptrends	0.0407*	
All three outcomes		0.0625*
Critical value	0.0225	0.0275
Pattern 1324		
Uptrends vs. downtrends	0.0641*	
Downtrends vs. flats	0.0347*	
Flats vs. uptrends	0.0472*	
All three outcomes		0.0641*
Critical value	0.0305	0.0372

* statistically significant at the 5 percent level.

profitable patterns by employing two nonparametric tests, the Kolmogorov–Smirnov test and the Birnbaum–Hall test, to identify whether or not the samples based on candlestick patterns are drawn from the same population distribution. After these tests, we can confirm the importance of trends prior to patterns, and return series are yielded from different and independent populations. Under the Kolmogorov–Smirnov test, the hypotheses are:

Hypothesis$_0$: *$F(x) = G(x)$ for all x from $-\infty$ to $+\infty$.*

Hypothesis$_1$: *$F(x) \neq G(x)$ for at least one value of x.*

$F(x)$ and $G(x)$ indicate two population distributions. The Kolmogorov–Smirnov statistic, T, is defined as:

$$T = \max \mid D_1(x) - D_2(x) \mid,$$

where $D(x)$ indicates the sample distributions.

The Birnbaum–Hall test uses the maximum results of the pair-wise Kolmogorov–Smirnov tests (see Conover 1980, p. 377). As shown in Table 5, our test results reveal that accurate signals from uptrend, downtrend, and flat markets for patterns 1234 and 1324 are drawn from different statistical distributions. This would be convincing evidence that the probability of positive profits yielded from the two patterns is not random.

According to our empirical results, investors could buy stocks following pattern 1234 in downtrend markets and pattern 1324 in uptrend markets. The holding periods are suitable for five and ten days—more specifically, when pattern 1234 (or 1324) occurs, checking the trend before the pattern, buying the stock at its opening price on the next day, and holding it for five or ten days to sell out.

Conclusions

The results of this study demonstrate that candlestick analysis has value for investors. This appears to violate the efficient markets hypothesis. We find that the candlestick technique has predictive power in the Taiwan stock market. Our findings, however, contradict Nison (1991). We find that all six two-day reversal patterns introduced in his book have no profitability. Nevertheless, some new patterns (bullish patterns 1234 and 1324) are profitable. Pattern 1234 can be regarded as the reversal pattern, and it agrees with contrarian strategies. Pattern 1324 can be classified into the continuation pattern, and it is suitable for momentum strategies. The observed return reversals are probably caused by overreaction (Wang and Xie 2010). Underreaction seems to enable momentum strategies to profit (Liu et al. 1999). Our asymmetric results are consistent with previous studies, such as those of Brock et al. (1992) and Lai et al. (2010), who find that buying signals generally produce higher average returns than selling signals.

Although the present study enhances the previous studies' findings by providing a much more detailed examination of two-day candlestick patterns, it has some limitations. For one thing, we are not concerned here with the "shadows" that represent the volatility of a trading day. Moreover, we do not consider the confirmative determinants of candlestick patterns, such as volume. Nevertheless, we believe that we have demonstrated a systematic method of research for studying the value of candlestick patterns.

Note

1. The skewness of returns for one day is 0.18; for five days, –0.09, and for ten days, –0.02.

References

Beja, A., and M.B. Goldman. 1980. "On the Dynamic Behavior of Prices in Disequilibrium." *Journal of Finance* 35, no. 2: 235–248.
Benartzi, S., and R.H. Thaler. 1995. "Myopic Loss Aversion and the Equity Premium Puzzle." *Quarterly Journal of Economics* 110, no. 1: 73–94.
Blume, L.; D. Easley; and M. O'Hara. 1994. "Market Statistics and Technical Analysis: The Role of Volume." *Journal of Finance* 49, no. 1: 153–181.
Brock, W.; J. Lakonishok; and B. LeBaron. 1992. "Simple Technical Trading Rules and Stochastic Properties of Stock Returns." *Journal of Finance* 47, no. 5: 1731–1764.
Brown, D.P., and R.H. Jennings. 1989. "On Technical Analysis." *Review of Financial Studies* 2, no. 4: 527–551.
Caginalp, G., and H. Laurent. 1998. "The Predictive Power of Price Patterns." *Applied Mathematical Finance* 5, nos. 3–4: 181–205.
Clyde, W.C., and C.L. Osler. 1997. "Charting: Chaos Theory in Disguise?" *Journal of Future Markets* 17, no. 5: 489–514.
Conover, W.J. 1980. *Practical Nonparametric Statistics.* 2d ed. New York: Wiley.
———. 1999. *Practical Nonparametric Statistics.* 3d ed. New York: Wiley.
De Long, B.; A. Shleifer; L. Summers; and R. Waldmann. 1990. "Noise Trader Risk in Financial Markets." *Journal of Political Economy* 98, no. 4: 703–738.
Fama, E.F. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25, no. 2: 383–418.
Froot, K.A.; D.S. Scharfstein; and J.C. Stein. 1992. "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation." *Journal of Finance* 47, no. 4: 1461–1484.
Fock, J.H.; C. Klein; and B. Zwergel. 2005. "Performance of Candlestick Analysis on Intraday Futures Data." *Journal of Derivatives* 13, no. 1: 28–40.
Goldbaum, D. 2003. "Profitable Technical Trading Rules as a Source of Price Instability." *Quantitative Finance* 3, no. 3: 220–229.
Goo, Y.; D. Chen; and Y. Chang. 2007. "The Application of Japanese Candlestick Trading Strategies in Taiwan." *Investment Management and Financial Innovations* 4, no. 4: 49–71.
Grundy, B.D., and M. McNichols. 1989. "Trade and the Revelation of Information Through Prices and Direct Disclosure." *Review of Financial Studies* 2, no. 4: 495–526.

Hellwig, M. 1982. "Rational Expectations Equilibrium with Conditioning on Past Prices: A Mean–Variance Example." *Journal of Economic Theory* 26, no. 2: 279–312.
Horton, M.J. 2009. "Stars, Crows, and Doji: The Use of Candlesticks in Stock Selection." *Quarterly Review of Economics and Finance* 49, no. 2: 283–294.
Jegadeesh, N. 1990. "Evidence of Predictable Behavior of Security Returns." *Journal of Finance* 45, no. 3: 881–898.
Johnson, N.J. 1978. "Modified *t*-Tests and Confidence Intervals for Asymmetrical Populations." *Journal of the American Statistical Association* 73, no. 363: 536–544.
Kahneman, D., and A. Tversky. 1979. "Prospect Theory: An Analysis of Decision Under Risk." *Econometrica* 47, no. 2: 263–291.
Krausz, J.; S. Lee; and K. Nam. 2009. "Profitability of Nonlinear Dynamics Under Technical Trading Rules: Evidence from Pacific Basin Stock Markets." *Emerging Markets Finance and Trade* 45, no. 4: 13–35.
Lai, H.; C. Chen; and C. Huang. 2010. "Technical Analysis, Investment Psychology, and Liquidity Provision: Evidence from the Taiwan Stock Market." *Emerging Markets Finance and Trade* 46, no. 5: 18–38.
Lehmann, B.N. 1990. "Fads, Martingales, and Market Efficiency." *Quarterly Journal of Economics* 105, no. 1: 1–28.
Levy, R. 1971. "The Predictive Significance of Five-Point Chart Patterns." *Journal of Business* 44, no. 3: 316–323.
Liu, W.; N. Strong; and X. Xu. 1999. "The Profitability of Momentum Investing." *Journal of Business Finance and Accounting* 26, nos. 9–10: 1043–1091.
Lukac, L.P., and B.W. Brorsen. 1990. "A Comprehensive Test of the Futures Market Disequilibrium." *Financial Review* 25, no. 4: 593–622.
Malkiel, B. 1996. *A Random Walk Down Wall Street: Including a Life-Cycle Guide to Personal Investing.* New York: Norton.
Marshall, B.R.; M.R. Young; and R. Cahan. 2008. "Are Candlestick Technical Trading Strategies Profitable in the Japanese Equity Market?" *Review of Quantitative Finance and Accounting* 31, no. 2: 191–207.
Marshall, B.R.; M.R. Young; and L.C. Rose. 2006. "Candlestick Technical Trading Strategies: Can They Create Value for Investors?" *Journal of Banking and Finance* 30, no. 8: 2303–2323.
McKenzie, M.D. 2007. "Technical Trading Rules in Emerging Markets and the 1997 Asian Currency Crises." *Emerging Markets Finance and Trade* 43, no. 4: 46–73.
Morris, G. 1995. *Candlestick Charting Explained: Timeless Techniques for Trading Stocks and Futures.* New York: McGraw-Hill Trade.
Nison, S. 1991. *Japanese Candlestick Charting Techniques.* New York: Institute of Finance.
Park, C.H., and S.H. Irwin. 2007. "What Do We Know about the Profitability of Technical Analysis?" *Journal of Economic Surveys* 21, no. 4: 786–826.
Schmidt, A.B. 2002. "Why Technical Trading May Be Successful? A Lesson from the Agent-Based Modeling." *Physica A: Statistical Mechanics and Its Applications* 303, nos. 1–2: 185–188.
Shiu, Y., and T. Lu. 2011. "Pinpoint and Synergistic Trading Strategies of Candlesticks." *International Journal of Economics and Finance* 3, no. 1: 234–244.
Sullivan, R.; A. Timmermann; and H. White. 1999. "Data Snooping, Technical Trading Rule Performance, and the Bootstrap." *Journal of Finance* 54, no. 5: 1647–1691.
Wang, C., and L. Xie. 2010. "Information Diffusion and Overreaction: Evidence from the Chinese Stock Market." *Emerging Markets Finance and Trade* 46, no. 2: 80–100.