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Trend definition or holding strategy: What determines the profitability of candlestick charting?

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ABSTRACT

We ask what determines the profitability of candlestick trading strategies. Is it the definition of trend and/or the holding strategy that one uses in candlestick charting analysis? To answer this, we systematically consider three definitions of trend and four holding strategies. Applying candlestick trading strategies to the DJIA component data, we find that regardless of which definition of trend is used, eight three-day reversal patterns with a Caginalp–Laurent holding strategy are profitable when we set the transaction cost at 0.5% and after we account for data-snooping bias, while the patterns with a Marsha ll–Young–Rose holding strategy are not profitable. For sensitivity analysis, we also find that our results are not qualitatively changed on a lower transaction cost of 0.1%, or when we conduct the subsample analyses based on three equal periods and three distinct market conditions. When considering a more volatile market, evidence in favor of candlestick trading strategies is strengthened.

1. Introduction

Candlestick charting, originally developed by Munehisa Homma, was applied to rice futures contracts in the world's first futures market, the Dojima Rice Exchange in Osaka, Japan, in the early 1700s. It was then introduced to the West in 1991 by Nison (1991). Candlestick charting is distinct from other technical indicators by simultaneously utilizing open–high–low–close prices; in particular, candlestick charting can reflect not only the changing balance between supply and demand (Caginalp and Laurent, 1998), but also aspects of investor sentiment and psychology (Marshall et al., 2006). Candlestick charting is readily available because many financial information providers, such as Reuters, supply the up-to-date real-time and historical data needed to construct candlesticks.

Even though the long history of candlestick charting analysis, there is not much research on it, and there is no consensus regarding whether this approach is profitable. For example, Caginalp and Laurent (1998) claim that applying candlestick trading strategies on daily stock returns in S&P 500 stocks can result in profits compounding at an annual rate as high as 200%. The profitability of candlestick trading strategies is further confirmed by Goo et al. (2007), Lu et al. (2012) and Lu (2014). On the other hand, Marshall et al. (2006, 2008) and Horton (2009) find that candlestick trading strategies do not have any predictive value for major equity markets. In addition, Fock et al. (2005) and Duvinage et al. (2013) employ 5-min data to investigate the German bond futures market and the U.S. stock market, respectively, and both conclude that candlestick trading strategies do not improve investment performance. It is worthwhile to note that candlestick charting is best applied to daily charts, though it is operationally applicable on any timeframes, such as 5-min or hourly charts (Nison, 1991). The rationale behind this claim is that a candle is mainly constructed by the daily opening and closing prices, which reflect investors' reactions or sentiments to the overnight information, rather than

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immediate reactions at every instant in time.[1] Consequently, most of the candlestick studies are considered daily trading and are more likely to find evidence to support the profitability of candlestick trading strategies.

These mixed conclusions motivate us to find out what determines the profitability of candlestick trading strategies. Caginalp and Laurent (1998) mention three key components about studying candlesticks, i.e. categorizing patterns, identifying trends, and calculating profits. Among them, candlestick patterns are well-defined by Nison (1991) and the definitions of categorizing patterns are widely accepted. Therefore, we focus on the two issues that definitions often vary across studies. One is the definitions of trend in recognizing candlestick trading strategies, and the other is the holding strategies used in evaluating candlestick patterns.[2] We investigate three definitions of trend (MA_3, EMA_{10}, and *Levy*) and four holding strategies (*CL*-3, *MYR*-10, *CL*-10, and *MYR*-3). The details will be reported in Section 2.

Then, we apply the Stepwise Superior Predictive Ability (Step-SPA) test of Hsu et al. (2010) that is not subject to data-snooping bias to candlestick trading strategies. We find that eight reversal three-day patterns measured by the Caginalp–Laurent holding strategy appear to be profitable after we account for transaction costs at 0.5%. In contrast, the Marshall–Young–Rose holding strategy will not earn significant positive returns, and we obtain qualitatively similar results even when we lower the transaction cost in the analysis. The results regarding these holding strategies are not sensitive to the subsample analyses when we split the sample by three equal periods, or different market conditions. Furthermore, we examine the relatively volatile NASDAQ market as well, and the finding reveals that the magnitude of significant positive mean returns is even larger than in DJIA market. As a result, candlestick investors can realize greater profits when markets are more volatile, which is in line with the finding of Han et al. (2013). Most importantly, our results show that the holding strategies play a crucial role in determining successful trades, but the impact of various definitions of trend on the performance of candlestick trading strategies appears to be marginal.

While Duvinage et al. (2013) also consider data-snooping bias in their analysis, there are some differences in our research designs. First, they use high-frequency intraday 5-min data from April 1, 2010 to April 13, 2011, whereas we consider the daily data, from January 2, 1992 through December 31, 2012. We consider a much longer period and candlestick charting is more commonly analyzed in a daily framework (e.g., Nison, 1991; Marshall et al., 2006). Second, they adopt 83 rules defined by the TA-Lib MATLAB toolbox from one- to five-line patterns, which include reversal and continuation patterns, but we only focus on eight three-line reversal patterns, as in Caginalp and Laurent (1998).[3] Our approach is also different from those in Brock et al. (1992) and Marshall et al. (2006), where they apply the model-based bootstrap method to test the statistical significance of trading profits. In their approaches, they create simulated prices from widely used models for financial returns, and conditional returns from the simulated return series for each pattern are compared with returns conditional on trading rules from the original series. While model-based bootstrapping is easy to use, the method could be subject to the misspecification bias in the null models (Park and Irwin, 2007).

The remainder of this study is organized as follows. Section 2 outlines the design of this research. We report the main empirical results and carry out further checks for the robustness of the results in Section 3. Section 4 then concludes this work. The technical details of the Step-SPA test and the individual test are in Appendix.

2. Candlestick charting and research design

Due to the widespread use of candlestick trading strategies among traders and financial professionals, the reliability of this approach is of particular interest. Candlestick lines are constructed from four prices: the opening, high, low, and closing prices, as shown in Fig. 1.[4] The boxed area between the opening and closing prices is called the real body. If the closing price is higher than its opening price, the real body is white or hollow, suggesting that the session is bullish. If the closing price is lower than its opening price, the real body is then black or filled, indicating that the session is bearish. The length of the real body can show how dominant the demand or supply was during a trading session. The vertical lines drawn above and below the real body are the upper and lower shadows, respectively.

Caginalp and Laurent (1998) note that three key components should be recognized when studying candlestick trading strategies: (i) categorizing patterns, (ii) identifying trends, and (iii) holding strategies.

2.1. Candlestick patterns

In candlestick charting, many patterns consist of a specific sequence of single lines, and most discussed patterns are recognized within a three-line (three-day) time frame (Nison, 1991, 1994; Morris, 1995). Candlestick patterns are divided into two types: reversal patterns for a shift in trend and continuation patterns for persistence in the prevailing trend. Technical analysts argue that participants are inclined to sell at the peak and to buy at the bottom, and hence reversal patterns are more notable and meaningful (Nison, 1991; Brock et al., 1992; Lu et al., 2012). In practice, candlestick analysts place much more emphasis on reversal patterns than continuation ones (Nison, 1994), so we consider eight three-day reversal patterns in this study. These candlestick patterns can be further classified into bullish and bearish groups for buying and short-selling, respectively.

2.1.1. Bullish patterns after downtrends

Four bullish patterns are examined in this study: *Three White Soldiers* (*TWS*), *Three Inside Up* (*TIU*), *Three Outside Up* (*TOU*), and *Morning Star* (*MS*). The *TWS* pattern is composed of three long white candles which close at higher prices than opening, and starts during a downtrend. This pattern hints that the downtrend will reverse into an uptrend, and hence investors are suggested to buy into this stock. The pattern is defined below as a set of inequalities, in which P_i^o and P_i^c refer to the opening and closing prices.

[1] Morris (1995, p. 211–212) argues that "One must also keep in mind that candle patterns reflect the short term psychology of trading, including the decision process that occurs after a market is closed. This is why open and close prices are so important. Using intraday day data without the benefit of a break is questionable at the very least." Furthermore, Logan (2008, p. 15) adds that "The opening and closing prices of candles on intraday charts are not as significant as they are on the daily time frame…the open of one intraday period is usually not much different than the close of the prior period."

[2] Caginalp and Laurent's three key components should be categorizing patterns, identifying trends, and calculating profits. Here, we use the term "holding strategies" instead of "calculating profits". Note that these two are equivalent in the sense that different ways to calculate profits correspond to different holding strategies, as we discuss in Section 2.3 below.

[3] Morris (1992) tabulates a complete list of candlestick patterns, in which there are 32 reversal patterns, of which eight patterns are built by three-line formation.

[4] The term "candlestick line" is used to refer to any single candlestick during a specific period of trading session. For example, in a 5-min timescale, one line represents 5 min, while it indicates one day in a daily timescale.

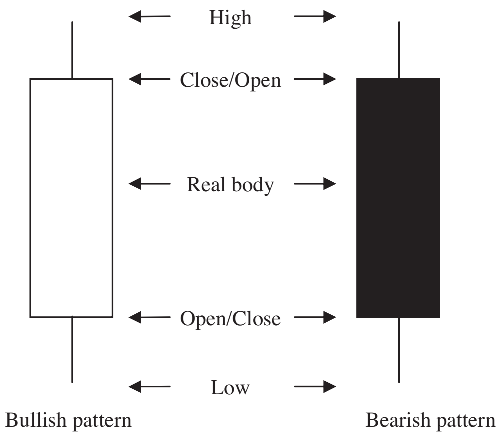

Fig. 1. Construction of a candlestick line. It consists of the opening, high, low, and closing prices. Each candlestick line represents one period (a day, an hour, a minute, etc.) of data.

$$P^c_i > P^o_i \quad \text{for } i = \text{day 1, day 2, day 3;}$$
$$P^c_{\text{day3}} > P^c_{\text{day2}} > P^c_{\text{day1}};\ P^c_{\text{day1}} > P^o_{\text{day2}} > P^o_{\text{day1}};\ P^c_{\text{day2}} > P^o_{\text{day3}} > P^o_{\text{day2}}.$$

During a downtrend, the *TIU* pattern is composed of three candles, the first one continues the downtrend with a long black candle, the second one is a small white line showing the brake of the trend, and the third one closes at a price that is higher than the opening of the first. The *TIU* pattern is also a bullish reversal pattern for buying. The pattern is defined below.

$$P^o_{\text{day1}} > P^c_{\text{day1}};\ P^o_{\text{day1}} \geqslant P^o_{\text{day2}} > P^c_{\text{day1}};$$
$$P^o_{\text{day1}} > P^c_{\text{day 2}} \geqslant P^c_{\text{day1}};\ P^c_{\text{day3}} > P^o_{\text{day3}} \text{ and } P^c_{\text{day3}} > P^o_{\text{day1}}.$$

The *TOU* pattern is similar to the *TIU* pattern. During a downtrend, the first candle is a small black one revealing a good match between supply and demand, while the second and third ones show that demand from buyers is increasing. The pattern is shown below.

$$P^o_{\text{day1}} > P^c_{\text{day1}};\ P^c_{\text{day2}} > P^o_{\text{day1}} > P^c_{\text{day1}} > P^o_{\text{day2}};$$
$$P^c_{\text{day3}} > P^o_{\text{day3}} \text{ and } P^c_{\text{day3}} > P^c_{\text{day2}}$$

The principle of the *MS* pattern is that the downtrend continues with a long black candle, and the second day confirms the pessimistic market conditions with a downward gap (the second candle can be black or white). Finally, the third day closes at the highest price of all three days. The pattern is shown below.

$$P^o_{\text{day1}} > P^c_{\text{day1}};\ \left|P^o_{\text{day2}} - P^c_{\text{day2}}\right| > 0;\ P^c_{\text{day1}} > P^c_{\text{day2}} \text{ and } P^c_{\text{day1}} > P^o_{\text{day2}};$$
$$P^c_{\text{day3}} > P^o_{\text{day3}} \text{ and } P^c_{\text{day3}} > P^c_{\text{day1}} + \left(P^o_{\text{day1}} - P^c_{\text{day1}}\right)/2.$$

2.1.2. Bearish patterns after uptrends

The bearish patterns investigated in this work are *Three Black Crows* (*TBC*), *Three Inside Down* (*TID*), *Three Outside Down* (*TOD*), and *Evening Star* (*ES*). The *TBC* pattern is composed of three long black candlesticks which all close at lower prices than the opening, and it starts after an uptrend. This pattern reveals that the uptrend will end, and hence investors are recommended to short-sell. The pattern is shown below.

$$P^o_i > P^c_i \quad \text{for } i = \text{day 1, day 2, day 3;}$$
$$P^c_{\text{day1}} > P^c_{\text{day2}} > P^c_{\text{day3}};\ P^o_{\text{day1}} > P^o_{\text{day2}} > P^c_{\text{day1}};\ P^o_{\text{day2}} > P^o_{\text{day3}} > P^c_{\text{day2}}.$$

The *TID* pattern is the mirror image of the *TIU* pattern. The first candle, a long white one, continues the uptrend, the second one is a small black line that warns of the end of the uptrend, and the third one closes at a price that is lower than the opening of the first.[5] The *TID* pattern is a bearish reversal pattern for short-selling. The pattern is shown below.

$$P^c_{\text{day1}} > P^o_{\text{day1}};\ P^c_{\text{day1}} > P^o_{\text{day2}} \geqslant P^o_{\text{day1}};$$
$$P^c_{\text{day1}} \geqslant P^c_{\text{day2}} > P^o_{\text{day1}};\ P^o_{\text{day3}} > P^c_{\text{day3}} \text{ and } P^o_{\text{day1}} > P^c_{\text{day3}}.$$

The *TOD* pattern is the opposite of the *TOU* pattern. During an uptrend, the first line is a small white line, revealing the good match between supply and demand, and the second and third ones are downward stair-steps. The pattern is shown below.

$$P^c_{\text{day1}} > P^o_{\text{day1}};\ P^o_{\text{day2}} > P^c_{\text{day1}} > P^o_{\text{day1}} > P^c_{\text{day2}};$$
$$P^o_{\text{day3}} > P^c_{\text{day3}} \text{ and } P^c_{\text{day3}} < P^c_{\text{day2}}$$

The *ES* pattern can be also regarded as an inversion of the *MS* pattern. The first line is a long white candle, and the second day continues the bullish atmosphere of the market with an upward gap (the second line can be black or white). Finally, the investors leave the market with a long black line, giving a bearish reversal signal. The pattern is shown below.

$$P^c_{\text{day1}} > P^o_{\text{day1}};\ \left|P^o_{\text{day2}} - P^c_{\text{day2}}\right| > 0;\ P^c_{\text{day2}} > P^c_{\text{day1}} \text{ and } P^c_{\text{day2}} > P^o_{\text{day1}};$$
$$P^o_{\text{day3}} > P^c_{\text{day3}} \text{ and } P^c_{\text{day3}} < P^o_{\text{day1}} + \left(P^c_{\text{day1}} - P^o_{\text{day1}}\right)/2.$$

The configurations of the aforementioned patterns are presented in Fig. 2.

2.2. Trend definitions

Candlestick patterns play a crucial role in signaling whether a trend will continue or reverse. A trend is defined as the way that the price gradually moves, and the direction of the trend is the key determinant of a successful trade. Both Nison (1991) and Morris (1995) emphasize that it is not appropriate to use a candlestick pattern as a trading signal if a trend is not properly defined.

The current study not only examines which candlestick patterns are the catalysts of trend reversals, but also compares their effectiveness based on various trends. Previous studies adopt different definitions of trend with regard to candlestick trading strategies. Here we consider three definitions.

The first trend we consider is the MA_3 trend, which is a three-day moving average over six days.[6] This is introduced by Caginalp and Laurent (1998), and they claim that their mathematical method can avoid the parametric problem and can accurately capture the concept of a trend. Therefore, Goo et al. (2007), Horton (2009), and Lu (2014) follow the same method to define trends in their works. Specifically, the three-day moving average on day t is defined by

$$MA_{3,t} = \frac{1}{3}\sum_{i=0}^{2} P^c_{t-i} \tag{1}$$

An uptrend is then defined by

$$MA_{3,t-6} < MA_{3,t-5} < \cdots < MA_{3,t-1} < MA_{3,t} \tag{2}$$

A downtrend is defined by

$$MA_{3,t-6} > MA_{3,t-5} > \cdots > MA_{3,t-1} > MA_{3,t} \tag{3}$$

[5] With regard to the definitions of the following three patterns, *TID*, *MS*, and *ES*, Caginalp and Laurent (1998) are inconsistent with their figures. Following Nison (1991) and Morris (1995), these patterns are correctly defined in the current study.

[6] Another similar trend is fine-tuned by Lu et al. (2012) from a three-day moving average to a five-day one, and the results based on these two definitions are almost the same.

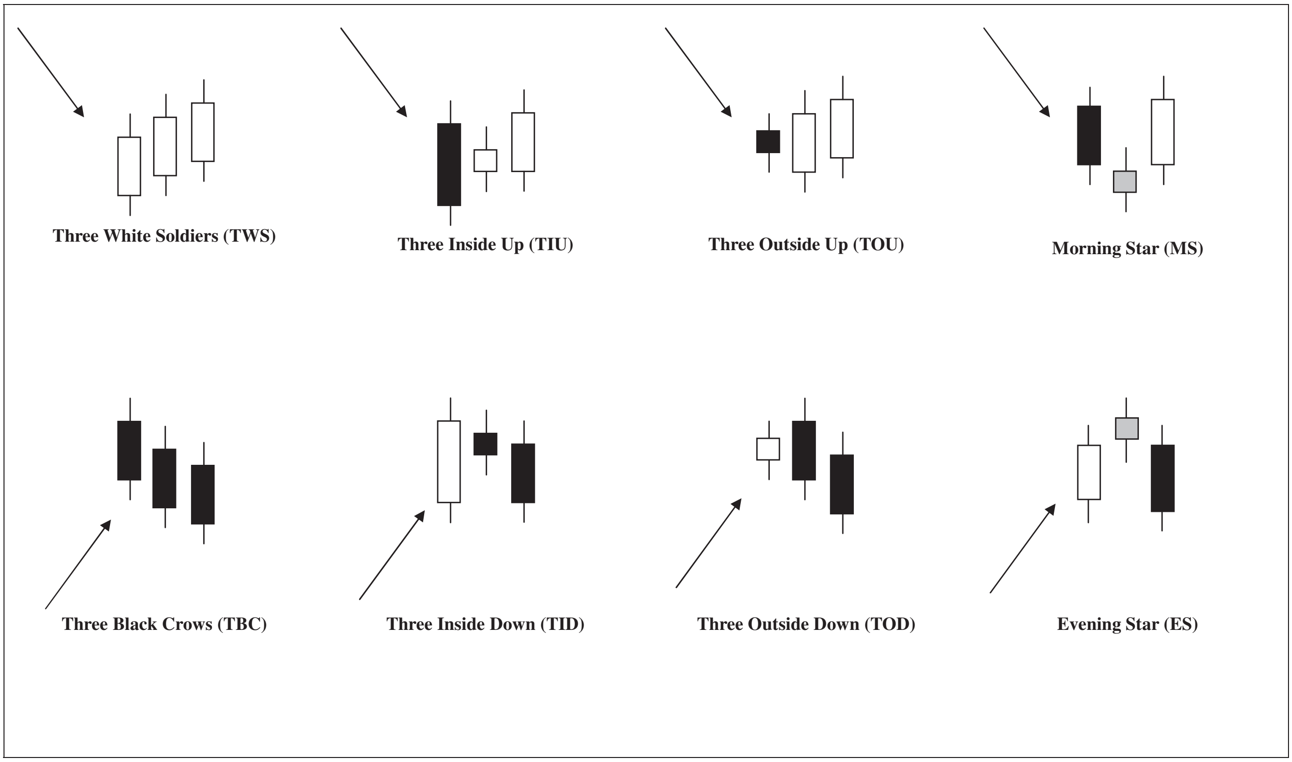

Fig. 2. Illustration of eight three-day reversal candlestick patterns. Each candlestick chart displays a pattern after an uptrend or a downtrend.

The second type of trend is the EMA_{10} trend proposed by Marshall et al. (2006), and is also used in Marshall et al. (2008). The EMA_{10} trend is defined as a ten-day exponential moving average of closing prices, as follows:

$$EMA_{10,t} = \alpha P_t^c + (1-\alpha)EMA_{10,t-1} \tag{4}$$

where $\alpha = 2/(10+1)$

When the closing price is more (less) than EMA_{10}, the trend is upward (downward), and the key feature of EMA_{10} is that market conditions are always alternating, moving either up or down.

The third type of trend, called the *Levy* trend in this paper, is introduced in Levy (1971), which provides the first definition of trend in the literature. In his approach, the reversal point of the trend can be identified by the slope of a linear formula which determines the percentage incremental price move. He takes the average changes of day-to-day closing prices over the most recent 131 days, and an uptrend is defined as

$$\frac{P_t^c - P_{t-6}^c}{P_{t-6}^c} > 6\theta \tag{5}$$

where θ refers to the average changes of day-to-day closing prices over the most recent 131 days.

2.3. Holding strategy

Conceptually, the holding strategy involves two things: the exit strategy and the holding period. Various holding strategies are used in previous studies, and to date there is no unanimous agreement upon the definition of the profitability of candlestick trading strategies. To the extent that the predictive ability of candlestick patterns hinges on the holding strategies adopted, it is sensible to investigate the impact of competing strategies on the performance of candlestick trading strategies.

In general, there are two approaches to comparing the returns yielded by candlestick trading strategies. One is the Caginalp–Laurent (*CL*) exit strategy proposed by Caginalp and Laurent (1998), and the other is the Marshall–Young–Rose (*MYR*) exit strategy offered by Marshall et al. (2006). The *CL* exit strategy is an average of the exit prices over the holding period, and the investors can make an equal-weight exit with this period. However, the *MYR* exit strategy sets a specific day to exit the market, which seems rather arbitrary.[7] With regard to holding periods, we consider the typical timescales of three and ten days. This leads to a total of four holding strategies, as follows:[8]

$$R_{CL\text{-}3} = \frac{(P_{t+4}^c + P_{t+5}^c + P_{t+6}^c)/3 - P_{t+4}^o}{P_{t+4}^o} \times 100\% \tag{6}$$

$$R_{MYR\text{-}10} = \ln\left(\frac{P_{t+13}^c}{P_{t+4}^o}\right) \times 100\% \tag{7}$$

$$R_{CL\text{-}10} = \frac{\frac{1}{10}\sum_{i=t+4}^{t+13} P_i^c - P_{t+4}^o}{P_{t+4}^o} \times 100\% \tag{8}$$

$$R_{MYR\text{-}3} = \ln\left(\frac{P_{t+6}^c}{P_{t+4}^o}\right) \times 100\% \tag{9}$$

To be specific, the $R_{CL\text{-}3}$ holding strategy, introduced by Caginalp and Laurent (1998), indicates that one buys one unit at the beginning of period $t+4$ and sell one-third of it at the end of periods, $t+4$, $t+5$ and $t+6$. In contrast, the $R_{MYR\text{-}10}$ holding strategy proposed by Marshall et al. (2006) suggests that one buys one unit

[7] It is conceivable that the trading rule is not profitable based on the Marshall–Young–Rose formula when the market has been promising but suddenly experiences a slump in the tenth day.

[8] For example, both Marshall et al. (2006) and Marshall et al. (2008) examine the returns of a ten-day holding period. Goo et al. (2007) compare the returns day by day when positions are held for one to ten days. Lu (2014) specifically considers the profit of the first and the tenth days.

at the beginning of period $t + 4$ and sells it all at the end of period $t + 13$. For further comparison, we extend Formulas (6) and (7) to ten- and three-day frameworks, respectively, as shown in Formulas (8) and (9), and call them the *CL*-10 holding strategy and the *MYR*-3 holding strategy.[9]

2.4. Transaction cost

Park and Irwin (2007) emphasize the importance of transaction costs when studying technical analysis, and state that these generally consist of two components, brokerage commissions and bid-ask spreads. Caginalp and Laurent (1998) note that the largest cost in the U.S. stock market is the bid-ask spread, which ranges from 0.1% to 0.3%, since commissions are negligible, at about \$20 for several thousand shares. Therefore, we assume that the total transaction costs are 0.5% per round turn, and an adjustment is made for this with all the results in this study.[10] We assume a higher transaction cost than previous studies for one main reason: if a trading rule is profitable in our setup with a higher transaction cost, then it must be profitable in other frameworks, and hence we are taking a more conservative approach.

We adjust for transaction costs to define realized returns as equal to original returns minus 0.5%. In Eq. (6), for example, if the selling price (opening price of $t + 4$) is 100, and the closing prices of $t + 4$, $t + 5$, and $t + 6$ are 102, 99.5, and 104.5, respectively, then the return based on Eq. (6) is 2%. For a long position, the transaction-cost-adjusted return is 1.5%, whereas for a short position it is −2.5%. Similarly, the transaction-cost-adjusted returns can be calculated for other holding strategies.

2.5. Multiple hypotheses testing

While data-snooping bias is an important issue for empirical studies, the problem has gone largely unnoticed in the context of evaluating technical analysis. This bias occurs when one evaluates a set of technical rules to find profitable ones, and, by chance alone, it is likely that one will conclude that some of the rules are profitable, even if they do not have any genuine investment value. While a number of methods have been proposed to deal with data-snooping bias, we consider the Step-SPA test of Hsu et al. (2010) most suitable for our analysis for several reasons. First, even if the Reality Check of White (2000) and the Superior Predictive Ability test of Hansen (2005) can detect whether there exist trading rules that can generate positive expected returns, they cannot identify which rules these are. Second, even if the Stepwise Reality Check test of Romano and Wolf (2005) can identify the superior rules while controlling the asymptotic familywise error rate (FWER), the probability of rejecting at least one correct null hypothesis, it employs the least favorable configuration to construct its critical values, which makes the resulting test less powerful. The Step-SPA adopts the recentering method developed by Hansen (2005) to avoid the use of the least favorable configuration, and has been shown to be more powerful than the Stepwise Reality Check test in identifying profitable trading rules, while controlling the FWER well.

For $k = 1,\ldots,m$, define $d_{k,t} = \delta_{k,t-1}(R_t - \delta_{k,t-1}T_c)$ where R_t is the profit measure of a holding strategy at time t, T_c is the transaction cost, and $\delta_{k,t-1}$ is the trading signal generated by the k-th trading rule at time $t-1$, with the assigned value of 1 indicating a long position, -1 a short position and 0 no position. It should be noted that for bullish patterns, $\delta_{k,t-1}$ only takes on 1 and 0, and for bearish patterns, $\delta_{k,t-1}$ only takes on -1 and 0. Therefore, $d_{k,t}$ is the realized transaction-cost-adjusted return of the k-th trading rule at time t, which is serially correlated because the pair of series depends on the same r_t. Suppose that for each k, $E(d_k) = \mu_k$. The question of interest is to identity the set of trading rules that yield positive mean returns. Accordingly, we can formally establish the null hypotheses as follows:

$$H_0^k : \mu_k \leqslant 0, \quad k = 1, \ldots, m. \tag{10}$$

Note that when $\delta_{k,t-1} = 1, d_{k,t} = R - T_c$; when $\delta_{k,t-1} = 0, d_{k,t} = 0$; and when $\delta_{k,t-1} = -1, d_{k,t} = -R - T_c$.

For ease of reading, we offer the details of Step-SPA tests of Hsu et al. (2010) in Appendix. For comparison, we also summarize the individual test in Appendix.

3. Data and empirical results

3.1. Main results

This study employs a daily sample from 30 component stocks of the DJIA index for the period from January 2, 1992 to December 31, 2012. Stocks that failed to exist for the whole period are excluded, and hence the resulting sample includes 26 stocks. We first present the preliminary results with the aim of exploring the performance of eight three-day reversal patterns with regard to their predictive power (or profitability). The test statistics are calculated based on Eq. (11), and the null hypotheses are defined in Eq. (10).[11] When implementing the Step-SPA test, we set the number of bootstraps to $B = 10{,}000$ and the parameter of the geometric distribution to $Q = 0.9$, as in Sullivan et al. (1999) and Hsu et al. (2010), which reflects the highly dependent realized return of the trading rules.[12]

Tables 1 through Table 4 present the results for combinations of three definitions of trend and four types of holding strategies. Recall that the transaction cost we consider is 0.5%. For the *CL*-3 holding strategy reported in Table 1, all eight reversal patterns earn statistically significant positive returns across three trend definitions. For example, the *TWS* pattern earns mean returns after transaction costs of 0.23%, 0.45% and 0.19% for holding periods of three days with regard to three different definitions of the trend, respectively. We also report two widely used metrics for measuring the risk of losses in trading rules. The maximum drawdowns vary in a wide range, from a low of −0.75% to a high of −72.79%. It appears that the EMA_{10} trend tends to have larger values of the maximum drawdowns, whereas the *Levy* trend has lower maximum drawdowns. On the other hand, if the *MYR*-10 and the *MYR*-3 holding strategies are adopted (see Tables 2 and 4), all eight patterns, except for the *MS* in *MYR*-10 with the MA_3 trend definition and the *ES* in *MYR*-10 for the EMA_{10} trend definition, are unable to produce positive results, with the returns being either negative or insignificant for all three trend definitions. It is interesting to note that the use of an average profit measure seems

[9] It should be emphasized that the holding period is independent of the trend. For the candlestick signals to be valid, the trend has to be seen in the market preceding the formation of candlestick patterns, for example, bullish patterns occur only after the end of a significant downtrend. Candlestick patterns cannot be used as stand-alone indicators capable of generating operational trading signals. After trading signals are employed, the candlestick investor's profit is measured based on his/her holding strategies. Therefore, holding periods of 3 or 10 days are not affected by the preceding trend.

[10] For the U.S. stock market, transaction costs are commonly assumed to be 0.1–0.39% per round trade (see, e.g., Caginalp and Laurent, 1998; Sullivan et al., 1999; Bessembinder and Chan, 1998).

[11] Please see Appendix for details of the implementation of the Step-SPA and individual tests.

[12] When considering different values of the geometric parameter, such as $Q = 0.5$ and 0.7, we obtain the qualitatively similar results which do not alter the final conclusion. The results are not reported but are available upon request.

Table 1
Comparative results: CL-3.

Patterns	No.	Mean return (%)	*t*-Statistic	Winning (%)	VaR-1%	VaR-5%	Max drawdown (%)
Panel A. MA₃							
TWS	65	0.23*§	0.93	53.85	−6.54	−3.01	−6.54
TIU	84	1.91*§	4.93	80.95†	−5.96	−1.65	−5.96
TOU	93	1.11*§	3.88	69.89†	−8.29	−2.24	−8.29
MS	271	2.36*§	11.23	91.51†	−0.87	−0.20	−1.04
TBC	138	0.37*§	2.92	57.25	−5.10	−1.92	−5.10
TID	105	1.20*§	6.10	80.00†	−1.83	−0.81	−1.83
TOD	126	0.81*§	4.36	64.29†	−3.90	−1.91	−3.90
ES	383	1.41*§	10.55	85.12†	−0.73	−0.39	−2.24
Panel B. EMA₁₀							
TWS	244	0.45*§	3.16	55.74	−6.54	−2.28	−9.71
TIU	722	1.50*§	12.63	83.10†	−5.21	−1.09	−33.39
TOU	586	0.89*§	7.53	69.11†	−3.73	−1.63	−32.08
MS	1657	1.81*§	30.00	91.01†	−0.95	−0.20	−15.96
TBC	424	0.44*§	4.70	57.08†	−3.60	−1.80	−5.31
TID	680	1.17*§	14.39	76.47†	−2.19	−1.05	−7.04
TOD	759	0.78*§	11.26	67.33†	−3.26	−1.75	−9.35
ES	1969	1.65*§	20.64	88.78†	−0.71	−0.26	−2.24
Panel C. Levy							
TWS	20	0.19*§	0.53	40.00	−1.66	−1.66	−1.66
TIU	46	1.69*§	3.45	80.43†	−5.96	−2.45	−5.96
TOU	35	1.65*§	3.73	80.00†	−1.22	−0.74	−1.22
MS	87	2.78*§	6.41	91.95†	−0.99	−0.06	−0.99
TBC	39	0.09*§	0.27	46.15	−5.31	−4.36	−5.31
TID	32	0.88*§	3.22	75.00†	−1.19	−0.98	−1.19
TOD	32	0.73*§	1.95	71.88†	−3.90	−2.55	−3.90
ES	121	1.76*§	6.98	85.95†	−0.75	−0.29	−0.75

This table presents the results of the Step-SPA test in which three definitions of trend and four holding strategies are adopted. The term No. denotes the number of trades in each pattern. The *t*-statistics are based on Eq. (11), and the parameters of the Step-SPA test are: B = 10,000, Q = 0.9. *Indicates statistical significance based on the Step-SPA test at the 5% asymptotic familywise error rate (FWER). §Indicates statistical significance based on individual tests at the 5% significance level. Winning denotes the portion of the number of profitable trading in the total trades, and †indicates statistical significance based on binominal tests at the 5% level. Value at Risk (VaR)-α% is the maximum loss not exceeded with a given probability of $(1-\alpha)$, over a given period of time. Max drawdown is the maximum loss incurred from peak to bottom during a specified period of time.

Table 2
Comparative results: *MYR*-10.

Patterns	No.	Mean return (%)	*t*-Statistic	Winning (%)	VaR-1%	VaR-5%	Max drawdown (%)
Panel A. MA₃							
TWS	65	−0.09	−0.17	53.85	−12.99	−7.65	−12.99
TIU	84	−1.05	−1.63	42.86	−23.76	−9.34	−23.76
TOU	93	−1.51	−1.74	48.39	−37.76	−23.42	−37.76
MS	271	0.59*§	1.42	53.87	−23.09	−9.38	−37.90
TBC	138	−0.30	−0.66	49.28	−17.86	−9.20	−17.86
TID	105	0.05§	0.05	38.10†	−17.20	−6.97	−17.20
TOD	126	0.79§	0.74	42.06	−21.08	−9.56	−21.08
ES	383	−0.07	−0.21	45.95	−11.70	−8.60	−13.40
Panel B. EMA₁₀							
TWS	244	−0.49	−1.29	52.05	−29.81	−10.43	−35.33
TIU	722	−1.39	−4.66	44.94†	−33.23	−10.84	−72.79
TOU	586	−0.40	−1.70	48.98	−23.42	−8.71	−37.76
MS	1657	0.07§	0.43	53.75†	−17.81	−8.57	−49.84
TBC	424	−0.75	−2.46	41.27†	−18.49	−10.13	−24.18
TID	680	−0.55	−1.90	40.59†	−14.45	−9.34	−17.20
TOD	759	−0.81	−3.10	39.39†	−14.78	−10.08	−25.00
ES	1969	0.30*§	2.08	46.78†	−11.28	−7.34	−21.23
Panel C. Levy							
TWS	20	−0.53	−0.55	60.00	−10.50	−10.50	−10.50
TIU	46	−1.02	−1.04	41.30	−16.64	−13.07	−16.64
TOU	35	1.38§	1.40	57.14	−13.20	−10.01	−13.20
MS	87	0.77§	1.12	56.32	−20.63	−12.01	−20.63
TBC	39	−1.20	−1.07	33.33	−13.46	−13.15	−13.46
TID	32	−1.34	−0.82	37.50	−17.20	−14.23	−17.20
TOD	32	0.33§	0.30	37.50	−8.12	−7.03	−8.12
ES	121	0.63§	0.66	44.63	−19.42	−8.51	−19.42

This table presents the results of the Step-SPA test in which three definitions of trend and four holding strategies are adopted. The term No. denotes the number of trades in each pattern. The *t*-statistics are based on Eq. (11), and the parameters of the Step-SPA test are: B = 10,000, Q = 0.9. *Indicates statistical significance based on the Step-SPA test at the 5% asymptotic familywise error rate (FWER). §Indicates statistical significance based on individual tests at the 5% significance level. Winning denotes the portion of the number of profitable trading in the total trades, and †indicates statistical significance based on binominal tests at the 5% level. Value at Risk (VaR)-α% is the maximum loss not exceeded with a given probability of $(1-\alpha)$, over a given period of time. Max drawdown is the maximum loss incurred from peak to bottom during a specified period of time.

Table 3
Comparative results: *CL*-10.

Patterns	No.	Mean return (%)	*t*-Statistic	Winning (%)	VaR-1%	VaR-5%	Max drawdown (%)
Panel A. MA_3							
TWS	65	0.33*§	0.83	52.31	−8.71	−5.83	−8.71
TIU	84	2.02*§	3.71	69.05†	−11.32	−4.50	−11.32
TOU	93	0.71*§	1.35	66.67†	−22.30	−6.56	−22.30
MS	271	2.96*§	9.11	81.92†	−5.39	−2.23	−18.55
TBC	138	0.47*§	1.66	56.52	−9.42	−5.04	−9.42
TID	105	1.21*§	3.92	67.62†	−11.89	−2.82	−11.89
TOD	126	0.92*§	2.38	57.94	−8.98	−3.71	−8.98
ES	383	1.52*§	7.63	69.97†	−3.86	−2.40	−5.66
Panel B. EMA_{10}							
TWS	244	0.34*§	1.38	55.33	−16.94	−5.17	−24.62
TIU	722	1.29*§	7.02	69.32†	−10.36	−3.68	−18.31
TOU	586	0.97*§	5.24	66.38†	−6.84	−3.61	−22.30
MS	1657	2.08*§	20.92	78.19†	−5.64	−2.42	−16.24
TBC	424	0.34*§	1.92	54.25	−9.24	−4.87	−13.51
TID	680	1.06*§	7.54	62.65†	−6.29	−3.81	−11.89
TOD	759	0.51*§	4.07	57.58†	−8.16	−4.66	−15.41
ES	1969	1.83*§	17.35	72.73†	−4.04	−2.37	−7.93
Panel C. Levy							
TWS	20	−0.03	−0.05	45.00	−5.63	−5.63	−5.63
TIU	46	1.86*§	2.71	63.04	−6.95	−4.50	−6.95
TOU	35	2.64*§	3.48	88.57†	−1.37	−0.94	−1.37
MS	87	3.58*§	5.37	83.91†	−8.08	−3.38	−8.08
TBC	39	−0.53	−0.86	48.72	−10.99	−9.24	−10.99
TID	32	0.23§	0.42	56.25	−11.89	−2.01	−11.89
TOD	32	0.86*§	1.39	56.25	−3.89	−3.69	−3.89
ES	121	1.93*§	4.92	66.12†	−6.85	−2.47	−6.85

This table presents the results of the Step-SPA test in which three definitions of trend and four holding strategies are adopted. The term No. denotes the number of trades in each pattern. The *t*-statistics are based on Eq. (11), and the parameters of the Step-SPA test are: B = 10,000, Q = 0.9. *Indicates statistical significance based on the Step-SPA test at the 5% asymptotic familywise error rate (FWER). §Indicates statistical significance based on individual tests at the 5% significance level. Winning denotes the portion of the number of profitable trading in the total trades, and †indicates statistical significance based on binominal tests at the 5% level. Value at Risk (VaR)-α% is the maximum loss not exceeded with a given probability of $(1-\alpha)$, over a given period of time. Max drawdown is the maximum loss incurred from peak to bottom during a specified period of time.

to be much better than when a specific-day measure is used, and this also provides a reasonable explanation for the mixed conclusions with regard to candlestick trading strategies in the U.S. stock market. We can conclude that the holding strategy used is key to the effectiveness of candlestick charting, but the definition of trend does not appear to affect the results. Basically, the bullish patterns produce higher returns than the bearish ones. This finding agrees with prior studies, such as Brock et al. (1992), which report that buying signals generally produce higher average returns than selling signals. Moreover, the best result obtained with Levy's trend definition (3.58% shown in Table 3) seems to be consistent with the findings of Jegadeesh (1990) and Lehmann (1990), as they argue that a large positive and significant return can be earned when the stock price undergoes a very large reversal.

From a practical perspective, candlestick investors should adopt the *CL* holding strategy for the following reason: The profitability of the *CL* holding strategies is driven by the average measure of returns over the holding periods, which works as a mechanism for risk sharing,[13] whereas the *MYR* strategies determine the profit/loss solely by a specific day of exiting. This is likely to be the main reason for the superior performance of the *CL* holding strategies over the *MYR*-type. Therefore, candlestick charting is a highly applicable and profitable investment tool, and trading based on these patterns could be implemented in practice with moderate amounts of capital. In our example, if we initially invested a $1,000,000 trade by the *MS* pattern, we can turn this into a profit of $31,043,736 throughout the entire sample period, from 1992 to 2012.[14]

Tables 1 through 4 also highlight potential data-snooping bias. A number of trading rules are individually significant, but they are not jointly significant for the Step-SPA test when the FWER is 5%. For example, for the *MYR*-10 holding strategy with the MA_3 trend, *MS*, *TID* and *TOD* are statistically significant for individual *t*-tests at the 5% level, whereas only *MS* is able to reject the null hypothesis for the Step-SPA test at the 5% FWER. Without adjusting for data-snooping bias, one may conclude that there are more trading rules that are profitable with *MYR* holding strategies. This bias is also present in other cases;[15] in particular, four of the eight patterns considered in the *MYR*-10 holding strategy with the *Levy* trend are subject to data-snooping bias. Therefore, it appears that data-snooping problem is more likely to be present in the *MYR*-10 holding strategy, regardless of trend definitions.

We find that the eight three-day candlestick reversal patterns can create value for investors, which agrees with the use of a number of contrarian strategies (De Bondt and Thaler, 1985; Lo and Mackinlay, 1990; Jegadeesh and Titman, 1995) in behavioral finance. Fung and Lam (2004) argue that price reversals are due to the overreactions of investors. Similarly, Bloomfield and Hales (2002) claim that investors overreact more to trends that have previously occurred, which echoes the results found in this study. Therefore, our empirical findings also provide supportive evidence of investor overreactions in the market.

3.2. Robustness checks

In this section, we conduct a series of robustness checks. First, we examine whether the negative evidence of the *MYR* holding

[13] For example, candlestick investors adopting the *CL*-3 holding strategy will close one-third of their positions at each day over three days.

[14] The resulting profit is based on 1657 trading days that the *MS* pattern appeared during the sample period, with a total execution of 3300 trades; the first trade appeared on January 20, 1992 and the last one was on December 28, 2012. Details for this profit calculation are available upon request from the authors.

[15] These include the *MYR*-10 holding strategy with the EMA_{10} and *Levy* trend, the *CL*-10 holding strategy with the *Levy* trend, and the *MYR*-3 holding strategy with the MA_3 trend.

Table 4
Comparative results: *MYR*-3.

Patterns	No.	Mean return (%)	*t*-Statistic	Winning (%)	VaR-1%	VaR-5%	Max drawdown (%)
Panel A. MA_3							
TWS	65	−0.91	−1.95	33.85†	−17.55	−8.44	−17.55
TIU	84	−0.82	−2.32	35.71†	−11.35	−5.93	−11.35
TOU	93	−1.46	−2.48	44.57	−27.13	−9.63	−27.13
MS	271	0.20§	0.81	53.87	−13.64	−4.96	−30.80
TBC	138	−0.43	−1.62	41.30†	−11.50	−7.04	−11.50
TID	105	−0.65	−2.43	36.19†	−13.38	−5.23	−13.38
TOD	126	−0.36	−0.69	34.13†	−9.19	−5.71	−9.19
ES	383	0.02§	0.18	47.26	−5.23	−3.78	−7.61
Panel B. EMA_{10}							
TWS	244	−0.85	−3.26	41.80†	−12.71	−6.33	−37.74
TIU	722	−0.67	−4.43	40.78†	−8.88	−5.43	−37.45
TOU	586	−0.65	−4.64	40.44†	−9.14	−5.44	−30.09
MS	1657	−0.03	−0.34	50.82	−8.51	−4.14	−19.58
TBC	424	−0.36	−1.85	41.04†	−10.13	−5.61	−12.91
TID	680	−0.55	−3.48	39.71†	−8.63	−5.18	−15.49
TOD	759	−0.71	−4.95	37.81†	−8.85	−5.71	−18.22
ES	1969	0.13*§	1.76	47.13†	−6.82	−3.99	−10.42
Panel C. Levy							
TWS	20	−0.47	−1.12	40.00	−3.57	−3.57	−3.57
TIU	46	−1.01	−2.01	28.26†	−8.52	−6.79	−8.52
TOU	35	−0.48	−1.14	42.86	−5.58	−4.53	−5.58
MS	87	−0.30	−0.68	44.83	−17.88	−5.71	−17.88
TBC	39	−1.81	−3.03	28.21†	−12.91	−8.75	−12.91
TID	32	−1.55	−2.71	28.13†	−13.38	−5.21	−13.38
TOD	32	−0.24	−0.35	43.75	−7.24	−5.63	−7.24
ES	121	−0.38	−1.44	38.02†	−7.26	−4.97	−7.26

This table presents the results of the Step-SPA test in which three definitions of trend and four holding strategies are adopted. The term No. denotes the number of trades in each pattern. The *t*-statistics are based on Eq. (11), and the parameters of the Step-SPA test are: $B = 10{,}000$, $Q = 0.9$. *Indicates statistical significance based on the Step-SPA test at the 5% asymptotic familywise error rate (FWER). §Indicates statistical significance based on individual tests at the 5% significance level. Winning denotes the portion of the number of profitable trading in the total trades, and †indicates statistical significance based on binominal tests at the 5% level l. Value at Risk (VaR)-α% is the maximum loss not exceeded with a given probability of $(1-\alpha)$, over a given period of time. Max drawdown is the maximum loss incurred from peak to bottom during a specified period of time.

strategies is due to a higher transaction cost. Second, it is clearly observed that the DJIA index experienced long swings in the 1990s and the 2000s. The evidence in support of the *CL* holding strategies may well be affected by this. Additionally, we conduct two subsample analyses. We divide the full sample into three sub-samples with roughly equal lengths, and with different market conditions. Finally, we examine the profitability of candlestick trading strategies in the relatively volatile NASDAQ market.

3.2.1. Low transaction cost

In the preceding section, we consider a high transaction cost of 0.5%. However, one might argue that the trading rules with the *MYR* holding strategies cannot generate positive returns because a high transaction cost has been assumed. Therefore, we re-examine the results for the *MYR* holding strategies when the transaction cost is reduced to 0.1%, and the results are compared in Table 5. In general, the results are not quantitatively changed with respect to a lower transaction cost of 0.1%. For example, given the EMA_{10} trend, reducing the transaction cost would allow for only one more significant pattern being identified (*MS*) under the *MYR* holding strategies.

3.2.2. Sub-periods results

Two sub-sample analyses are carried out to examine the profitability of candlestick trading strategies; one considers three equal periods following Marshall et al. (2008), and the other takes three market conditions following Lu et al. (2012). Due to the numbers of trades available in each pattern, we restrict our discussion to the *CL*-3 holding strategy with the EMA_{10} trend in the following sub-sample study.

The results for the sub-samples are shown in Table 6. For the first part, the entire sample is equally divided into three sub-sample periods, 1992–1998, 1999–2005 and 2006–2012. As can be seen, all patterns produce significant and positive returns across three different periods, and the performance seems to be poor during the period 2006–2012.

3.2.3. Market condition results

Several studies, such as Pagan and Sossounov (2003), Lunde and Timmermann (2004), and Lu et al. (2012), discuss asymmetric stock returns in different market conditions. To check the results for different market conditions, as discussed in Lu et al. (2012), the performance of the eight reversal patterns is further examined by dividing the entire sample of the DJIA index into three sub-samples, including bull, bear, and oscillating markets. As shown in Fig. 3, the bull markets include three periods: 02 January 1992 to 30 July 1997, 13 March 2003 to 01 October 2007 and 06 March 2009 to 31 December 2012. The bear market includes one period, 02 October 2007 to 05 March 2009, and the oscillating market refers to 31 July 1997 to 12 March 2003. According to Panel B of Table 6, we find significant positive returns on the patterns regardless of market conditions. It is clear to see that all the patterns other than *TBC* in the bear market achieve returns greater than those that could be obtained in the bull markets. In particular, when the market is oscillating, the patterns always outperform as opposed to the bull markets. This is generally consistent with the well documented asymmetric stock returns.

3.2.4. NASDAQ results

A related question arises whether the candlestick trading strategies can make more profit in a riskier market. In particular, Han et al. (2013) find that moving average rules are more profitable on more volatile assets. To this end, we examine the profitability of candlestick trading strategies using NASDAQ 100 component stocks, where the major constituents of the exchange are technology and Internet stocks with high growth potential,

Table 5
Comparisons between two alternative transaction costs.

Patterns	No.	0.5%				0.1%			
		CL-3 Mean return	*MYR*-10 Mean return	*CL*-10 Mean return	*MYR*-3 Mean return	*CL*-3 Mean return	*MYR*-10 Mean return	*CL*-10 Mean return	*MYR*-3 Mean return
Panel A. MA_3									
TWS	65	0.23*	−0.09	0.33*	−0.91	0.63*	0.31	0.73*	−0.51
TIU	84	1.91*	−1.05	2.02*	−0.82	2.31*	−0.65	2.42*	−0.42
TOU	93	1.11*	−1.51	0.71*	−1.46	1.51*	−1.11	1.11*	−1.06
MS	271	2.36*	0.59*	2.96*	0.20	2.76*	0.99*	3.36*	0.60*
TBC	138	0.37*	−0.30	0.47*	−0.43	0.77*	0.10	0.87*	−0.03
TID	105	1.20*	0.05	1.21*	−0.65	1.60*	0.45	1.61*	−0.25
TOD	126	0.81*	0.79	0.92*	−0.36	1.21*	1.19	1.32*	0.04
ES	383	1.41*	−0.07	1.52*	0.02	1.81*	0.33	1.92*	0.42*
Panel B. EMA_{10}									
TWS	244	0.45*	−0.49	0.34*	−0.85	0.85*	−0.09	0.74*	−0.45
TIU	722	1.50*	−1.39	1.29*	−0.67	1.90*	−0.99	1.69*	−0.27
TOU	586	0.89*	−0.40	0.97*	−0.65	1.29*	0.00	1.37*	−0.25
MS	1657	1.81*	0.07	2.08*	−0.03	2.21*	0.47*	2.48*	0.37*
TBC	424	0.44*	−0.75	0.34*	−0.36	0.84*	−0.35	0.74*	0.04
TID	680	1.17*	−0.55	1.06*	−0.55	1.57*	−0.15	1.46*	−0.15
TOD	759	0.78*	−0.81	0.51*	−0.71	1.18*	−0.41	0.91*	−0.31
ES	1969	1.65*	0.30*	1.83*	0.13*	2.05*	0.70*	2.23*	0.53*
Panel C. Levy									
TWS	20	0.19*	−0.53	−0.03	−0.47	0.59*	−0.13	0.37*	−0.07
TIU	46	1.69*	−1.02	1.86*	−1.01	2.09*	−0.62	2.26*	−0.61
TOU	35	1.65*	1.38	2.64*	−0.48	2.05*	1.78*	3.04*	−0.08
MS	87	2.78*	0.77	3.58*	−0.30	3.18*	1.17*	3.98*	0.10
TBC	39	0.09*	−1.20	−0.53	−1.81	0.49*	−0.80	−0.13	−1.41
TID	32	0.88*	−1.34	0.23	−1.55	1.28*	−0.94	0.63*	−1.15
TOD	32	0.73*	0.33	0.86*	−0.24	1.13*	0.73	1.26*	0.16
ES	121	1.76*	0.63	1.93*	−0.38	2.16*	1.03	2.33*	0.02

This table presents the results of the Step-SPA test when two different levels of transaction costs are assumed. The term No. denotes the number of trades in each pattern. The parameters of the Step-SPA test are: $B = 10{,}000$, $Q = 0.9$. *Indicates statistical significance based on the Step-SPA test at the 5% asymptotic familywise error rate (FWER). The mean returns are in percentage.

Table 6
Sub-sample results.

Patterns	Sub-periods								
	No.	Mean return	*t*-Statistic	No.	Mean return	*t*-Statistic	No.	Mean return	*t*-Statistic
Panel A. By three equal periods									
	1992–1998			1999–2005			2006–2012		
TWS	60	0.27*§	1.03	103	0.49*§	2.07	81	0.52*§	2.28
TIU	207	1.51*§	6.56	288	1.72*§	7.86	227	1.21*§	8.32
TOU	143	1.12*§	3.84	233	0.87*§	4.16	210	0.76*§	6.07
MS	500	1.90*§	17.63	648	2.00*§	19.09	509	1.49*§	15.43
TBC	109	0.47*§	2.60	169	0.66*§	3.58	146	0.17*§	1.64
TID	180	1.15*§	7.80	259	1.35*§	8.96	241	0.98*§	8.36
TOD	219	0.83*§	6.07	276	0.90*§	7.26	264	0.62*§	6.14
ES	653	1.84*§	10.11	683	1.95*§	14.22	633	1.13*§	17.27
Panel B. By market conditions									
	Bull markets			Bear market			Oscillating market		
TWS	152	0.29*§	2.26	16	1.44*§	1.49	76	0.55*§	1.75
TIU	453	1.16*§	8.00	46	1.73*§	3.79	223	2.14*§	9.46
TOU	370	0.75*§	5.73	46	0.84*§	2.71	170	1.22*§	4.34
MS	1022	1.47*§	23.18	106	2.16*§	7.00	529	2.41*§	19.03
TBC	280	0.37*§	4.03	21	0.27*§	0.94	123	0.64*§	2.63
TID	424	0.87*§	10.46	45	1.54*§	3.83	211	1.67*§	9.34
TOD	495	0.65*§	8.56	49	0.85*§	2.86	215	1.08*§	6.80
ES	1309	1.26*§	14.61	100	2.27*§	8.21	560	2.44*§	13.11

This table presents the test results of the subsample analyses for the *CL*-3 holding strategy with the EMA_{10} trend. The term No. denotes the number of trades in each pattern. The *t*-statistics are based on Eq. (11), and the parameters of the Step-SPA test are: $B = 10{,}000$, $Q = 0.9$. *Indicates statistical significance based on the Step-SPA test at the 5% asymptotic familywise error rate (FWER). §Indicates statistical significance based on individual tests at the 5% significance level. The bull markets include three periods, 02 January 1992 to 30 July 1997, 13 March 2003 to 01 October 2007 and 06 March 2009 to 31 December 2012. The bear market runs from 02 October 2007 to 05 March 2009, and the oscillating market refers to 31 July 1997 to 12 March 2003. The mean returns are in percentage.

and are therefore typically more volatile than the DJIA market (see, e.g., Pástor and Veronesi, 2006). Likewise, we exclude stocks that ceased to exist during the sample period during (1992–2012), and hence the resulting sample remains 19 stocks. As shown in Table 7, the positive results broadly confirm the finding from the DJIA shown in Tables 1–4. The magnitude of positive mean returns is larger in NASDAQ than in DJIA market and the figures are statistically significant. For example, the *MS* pattern in the *CL*-3 holding

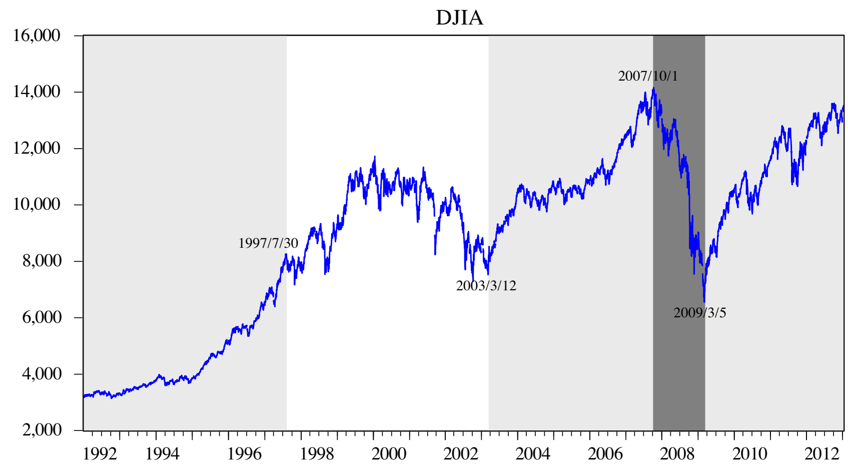

Fig. 3. Dow-Jones industrial average index for the period 02 January1992 through 31 December 2012. The light gray area denotes the bull-market periods: 02 January 1992–30 July 1997, 13 March 2003–01 October 2007 and 06 March 2009–31 December 2012. The dark gray area denotes the bear-market period: 02 October 2007–05 March 2009, and the white area denotes the oscillating-market period: 31 July 1997–12 March 2003.

Table 7
Comparative results: NASDAQ market.

Patterns	No.	*CL*-3		*MYR*-10		*CL*-10		*MYR*-3	
		Mean return	*t*-Statistic	Mean return	*t*-Statistic	Mean return	*t*-Statistic	Mean return	*t*-Statistic
Panel A. MA_3									
TWS	76	$1.45^{*\S}$	2.92	$0.09^{\S}$	0.13	$1.50^{*\S}$	2.52	$0.11^{\S}$	0.22
TIU	59	$3.53^{*\S}$	4.74	−2.24	−1.65	$3.63^{*\S}$	3.52	−0.71	−0.97
TOU	67	$2.66^{*\S}$	4.95	−1.47	−1.28	$2.59^{*\S}$	3.05	−0.86	−1.21
MS	213	$3.88^{*\S}$	10.36	$0.12^{\S}$	0.16	$4.05^{*\S}$	7.36	$0.28^{\S}$	0.67
TBC	110	$0.97^{*\S}$	3.35	$1.23^{\S}$	1.05	$1.62^{*\S}$	2.75	−0.31	−0.63
TID	69	$3.35^{*\S}$	3.78	−0.76	−0.80	$2.90^{*\S}$	3.00	−0.13	−0.22
TOD	129	$1.70^{*\S}$	5.29	−1.29	−1.60	$1.55^{*\S}$	2.98	−0.23	−0.44
ES	273	$2.44^{*\S}$	11.23	$0.19^{\S}$	0.25	$2.38^{*\S}$	6.98	$0.34^{\S}$	0.92
Panel B. EMA_{10}									
TWS	243	$1.10^{*\S}$	4.66	$0.07^{\S}$	0.16	$1.32^{*\S}$	3.89	−0.14	−0.46
TIU	521	$2.80^{*\S}$	14.01	−1.49	−3.11	$2.51^{*\S}$	8.74	−0.80	−3.14
TOU	545	$2.01^{*\S}$	11.75	−1.18	−2.64	$2.10^{*\S}$	8.10	−0.66	−3.29
MS	1360	$3.18^{*\S}$	26.84	$0.53^{*\S}$	2.15	$3.75^{*\S}$	21.60	$0.51^{*\S}$	3.96
TBC	401	$1.09^{*\S}$	6.41	$0.50^{\S}$	0.84	$1.16^{*\S}$	3.77	$0.10^{\S}$	0.28
TID	511	$2.58^{*\S}$	12.78	−0.68	−1.67	$2.31^{*\S}$	8.80	−0.01	−0.07
TOD	662	$1.37^{*\S}$	10.50	−0.86	−2.34	$1.12^{*\S}$	5.37	−0.81	−4.26
ES	1616	$2.65^{*\S}$	26.61	$0.64^{*\S}$	2.27	$2.80^{*\S}$	16.98	$0.61^{*\S}$	5.15
Panel C. Levy									
TWS	17	$0.50^{*\S}$	0.87	$0.13^{\S}$	0.13	$0.43^{\S}$	0.43	−2.07	−1.47
TIU	26	$3.46^{*\S}$	2.83	−3.76	−1.62	$2.54^{*\S}$	2.22	−0.76	−0.57
TOU	32	$2.62^{*\S}$	3.63	−1.70	−1.01	$2.82^{*\S}$	2.91	−0.67	−0.80
MS	81	$4.99^{*\S}$	6.60	$2.40^{*\S}$	1.92	$6.41^{*\S}$	5.46	$1.01^{\S}$	1.28
TBC	44	$1.19^{*\S}$	2.72	−1.41	−0.86	$0.09^{\S}$	0.10	−1.78	−2.02
TID	34	$3.67^{*\S}$	3.64	−3.76	−1.95	$2.32^{*\S}$	2.20	−1.12	−1.12
TOD	44	$1.61^{*\S}$	2.47	−1.64	−1.04	$1.39^{*\S}$	1.34	−1.74	−2.77
ES	113	$2.85^{*\S}$	7.41	$0.82^{\S}$	0.64	$2.58^{*\S}$	4.83	−0.04	−0.09

This table presents the results of the Step-SPA test in which three definitions of trend and four holding strategies are adopted. The term No. denotes the number of trades in each pattern. The *t*-statistics are based on Eq. (11), and the parameters of the Step-SPA test are: $B = 10{,}000$, $Q = 0.9$. *Indicates statistical significance based on the Step-SPA test at the 5% asymptotic familywise error rate (FWER). §Indicates statistical significance based on individual tests at the 5% significance level. The mean returns are in percentage.

strategy with the EMA_{10} trend earns mean returns after transaction costs of 1.81% and 3.18% for DJIA and NASDAQ market, respectively. Therefore, our results confirm the previous claim that the candlestick patterns are capable of generating more profits on a more volatile asset.

4. Conclusion

In this paper we provide a systematic analysis with three different definitions of trend and four possible holding strategies in candlestick research. There are two major findings in this study. First, the type of holding strategy plays a major role in the effectiveness of candlestick trading strategies. Second, this ancient trading strategy appears to possess predictive power with regard to asset returns. In particular, we find candlestick trading strategies can create better value for investors on riskier assets. We conduct a series of statistical diagnoses to test the statistical significance of trading profits. The Step-SPA test shows that our results are robust to potential data-snooping bias, and are not changed when we consider a battery of robustness checks.

Our findings confirm Caginalp and Laurent's (1998) study on the S&P 500 component stocks. These results lend some credence to the idea that a three-day holding period is better than a ten-day holding period, and the *CL* exit strategy is more suitable than the *MYR* exit strategy in candlestick trading strategies. While Marshall et al. (2006) and Marshall et al. (2008) claim that candlestick trading strategies have no value for investors, we present a different view, finding that candlestick trading strategies do help identify profitable trading opportunities. Even though candlestick trading strategies can be profitable, we note that there is no micro-foundation for candlestick charting analysis and for future research, it would be interesting and important to construct a micro-foundation for it.

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Appendix A

A1. Stepwise-SPA

The hypotheses in Eq. (10) involve multiple inequality constraints. The Step-SPA test is based on the following statistics:

$$\frac{\sqrt{T}d_1}{\hat{\sigma}_1}, \ldots, \frac{\sqrt{T}d_m}{\hat{\sigma}_m}, \tag{11}$$

where $\bar{d}_k = T^{-1}\sum_{t=1}^{T} d_{k,t}$ and T is the sample size. $\hat{\omega}_{k,k} = \hat{\sigma}_k^2$ is a consistent estimator for the long-run variance of $\lim_{T\to\infty}\text{var}(\sqrt{T}\bar{d}_k)$. Following Hansen (2005), the estimator proposed by Politis and Romano (1994) is used:

$$\hat{\omega}_{k,k} = \hat{\omega}_{k,0}^2 + \sum_{\ell=1}^{T-1} k(\ell, T)[\hat{\omega}_{k,\ell} + \hat{\omega}'_{k,\ell}],$$

where $\omega_{k,\ell} = T^{-1}\sum_{t=k+1}^{T}(d_{k,t} - \bar{d}_k)(d_{k,t-\ell} - \bar{d}_k)'$ and the weight function $k(\ell, T)$ is defined as

$$k(\ell, T) \equiv \frac{T-\ell}{T}(1-Q)^{\ell} + \frac{\ell}{T}(1-Q)^{T-\ell},$$

where Q is the parameter of the geometric distribution used in the stationary bootstrap defined below. This estimator is similar to that of Newey and West (1987), but with a different weight function.

To account for the weak dependence of the data, we use the stationary bootstrap of Politis and Romano (1994) to approximate the null distributions, and this is computed as follows. Let $d_t^*(b) \equiv d_{n_{b,t}}^*$, for $t = 1, \ldots, T$, be the b-th re-sample of d_t, where the indices $T_{b,1}, \ldots, T_{b,T}$ consist of blocks of $\{1, \ldots T\}$ with random lengths determined by the realization of a geometric distribution with the parameter $Q \in [0, 1)$. To be specific, $T_{b,1}$ is randomly chosen from $\{1, \ldots T\}$ with an equal probability assigned to each number. Second, for any $t > 1$, $T_{b,t} = T_{b,t-1} + 1$ with probability Q; otherwise, $T_{b,t}$ is chosen randomly from $\{1, \ldots T\}$.[16] A re-sample is done when T observations are drawn; let $\bar{d}^*(b) = \sum_{t=1}^{T} d_t^*(b)/T$ denote the sample average of this re-sample. Repeating this procedure B times yields an empirical distribution of $\bar{d}^*$ with B realizations.

Define the recentering parameter for the k-th trading rules as

$$\hat{\mu}_k = \bar{d}_k \cdot \mathbf{1}\left(\frac{\sqrt{T}\bar{d}_k}{\hat{\sigma}_k} \leqslant -\sqrt{2\log\log(T)}\right),$$

where $\mathbf{1}(\cdot)$ is the indicator function. Given the pre-specified level α_0, the bootstrapped SPA critical value is defined as follows:

$$\hat{q}_{\alpha_0}^* = \max(\hat{q}_{\alpha_0}, 0), \tag{12}$$

with $\hat{q}_{\alpha_0} = \inf\{q \big| P^*[\sqrt{T}\max_{k=1,\ldots,m}(\bar{d}_k^* - \bar{d}_k + \hat{\mu}_k)/\hat{\sigma}_k \leqslant q] \geqslant 1 - \alpha_0\}$, the $(1-\alpha_0)$-th quantile of the recentered empirical distribution, and P^* is the bootstrapped probability measure.

The Step-SPA test with the pre-specified level α_0 then proceeds as follows.

(1) Re-arrange $\bar{d}_k/\hat{\sigma}_k$ in a descending order.
(2) Reject the top model k if $\sqrt{T}\bar{d}_k/\hat{\sigma}_k$ is greater than $\hat{q}_{\alpha_0}^*(\text{all})$ the critical value bootstrapped as in Eq. (12) using the complete sample. If no model can be rejected, the procedure stops; otherwise, go to the next step.
(3) Remove $\bar{d}_k/\hat{\sigma}_k$ of the rejected models from the data. Reject the top model i in the sub-sample of remaining observations if $\sqrt{T}\bar{d}_k/\hat{\sigma}_k$ is greater than $\hat{q}_{\alpha_0}^*(\text{sub})$, the critical value bootstrapped as in Eq. (12) from the sub-sample. If no model can be rejected, the procedure stops; otherwise, go to the next step.
(4) Repeat the third step until no model can be rejected.

A2. Individual tests

For comparison, we also summarize how to test $H_0^k : \mu_k \leqslant 0$, for k = 1,…,m, individually. The individual test statistic is defined as $\sqrt{T}\bar{d}_k$. The individual critical value is defined as $c_{k,\alpha_0} = \inf\{c \big| P^*[\sqrt{T}(\bar{d}_k^* - \bar{d}_k) \leqslant c] \geqslant 1 - \alpha_0\}$, the $(1-\alpha_0)$- th quantile of the bootstrapped distribution of $\sqrt{T}(\bar{d}_k^* - \bar{d}_k)$. Then we will reject H_0^k if $\sqrt{T}\bar{d}_k > c_{k,\alpha_0}$.

[16] If $T_{b,t-1} = T$, we use the wrap-up procedure and set $T_{b,t} = 1$.

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