Can Price Anomalies been Obtained by Using Candlestick Patterns?

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Abstract

The aim of this study is to examine the predictive power of three-day candlestick patterns, improve performance by adopting a variable holding period approach, and identify two behavioral factors to explain the sources of profitability when using candlesticks. Using the Taiwan component stocks daily data for the period from 4 January 1992 to 31 December 2012, this study provides strong support for candlestick trading strategies, even when transaction costs are carefully taken into account. In addition, this study shows that candlestick charting can yield more substantial returns by using the variable holding period approach. Finally, trading volume per trade and turnover rates seem able to explain the profitability of using candlesticks.

JEL classification: G12; G14

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1. Introduction

Discoveries of ‘anomalies’ have been growing in the behavioral finance literature, which are based on irrational behavior (Kahneman and Tversky, 1979), disequilibriums (Beja and Goldman, 1980), feedback (De Long et al., 1990), market power (Froot et al., 1992), bubbles (Porter and Smith, 1994), noisy rational expectations (Blume et al., 1994), loss aversion (Benartzi and Thaler, 1995), chaos (Clyde and Osler, 1997), agent-based modeling (Schmidt, 2002), and instability (Goldbaum, 2003), as well as a number of other causes. In particular, Levy (1971), Treynor and Ferguson (1985) and Caginalp and Laurent (1998), among many others, examine the profitability of technical analysis in stock markets, and find that profitable trading rules do exist. These results suggest that technical analysis is useful not only because it has been widely applied by practitioners, but also because it provides evidence for the existence of anomalies.

Among various forms of technical analysis, candlestick charting is one of the most important and widely discussed. Candlestick charting is a trading signal producer based on the relationships among opening, high, low, and closing prices. It was first applied to the Japanese rice market in 1700s, and introduced to the U.S. in 1991 by Steve Nison. Nison (1991) claims that candlestick charting can be used to understand supply and demand in a market, and thus when an imbalance exists between these, this approach can identify profitable trading opportunities. Nowadays, most real-time financial information services, such as Reuters, provide up-to-date and detailed information about candlesticks, and this approach can even be implemented in MS Excel. With the increasing use of candlestick charting, it is thus necessary to find more effective ways to assess its profitability and increase its reliability.

This paper aims to examine the profitability of trading rules yielded by three-day candlestick patterns with two different definitions of trend, namely the three-day moving average over six inequalities (hereafter, MA_3), and closing prices above (or below) the ten-day exponential moving average (hereafter, EMA_{10}). As discussed in Caginalp and Laurent (1998), the definition of a trend plays a crucial role in determining the predictive power of candlesticks, and a three-day pattern itself without the correct trend is not as a useful indicator. However, most of the previous studies only apply one single trending procedure to evaluate candlestick patterns. For example, Caginalp and Laurent (1998), Goo et al. (2007), Lu and Shiu (2012), and Lu et al. (2012) adopt the definition of MA_3 and find strong support for the profitability of candlesticks, while Fock et al. (2005), Marshall et al. (2006), and Marshall et al. (2008) use the approach of EMA_{10} and reach the opposite conclusion.

These conflicting results indicate that one should be very cautious with regard to defining a trend. In addition, previous studies attempted to improve the profitability of candlestick patterns by using technical indicators (Fock et al., 2005) or stop-loss strategies (Goo et al., 2007). In this study, we consider an alternative method, namely the variable holding period approach, to improve on the profitability of using candlesticks.

In order to provide a more comprehensive discussion of the performance of candlestick patterns, this study extends the analysis of earlier works along the following lines. Firstly, we evaluate the profitability of candlestick patterns with two different definitions of trend, and demonstrate how such candlestick patterns can be applied to analyzing 154 stocks in the Taiwan stock market. Secondly, we also examine the performance of candlesticks by using the variable and fixed holding period approaches when transaction costs are taken into account. Thirdly, and most importantly, because the advocates of candlestick technical trading strategies assert that candlestick patterns can describe the psychological status of investors (Nison, 1991; Morris, 1995; Lu and Shiu, 2012), we also attempt to find out the sources of the profitability of candlesticks.

Our empirical results reveal several interesting features of the Taiwanese stock market. Firstly, based on the definition of MA_3, we find that two candlestick patterns possess genuine profitability of 1.49% and 0.86% by using the fixed holding period approach when transaction costs are considered. However, when the approach of EMA_{10} is adopted, the profitability of these two patterns falls significantly, to 0.86% and 0.57%, respectively. The finding that the approach of MA_3 performs better than that of EMA_{10} is mainly due to the definition of the trend. Secondly, if the variable holding period approach is employed and the approach of MA_3 is adopted, these two candlestick patterns can produce substantial returns of up to 11.77% and 1.35%, even when transaction costs are taken into account. This result shows that the variable holding period approach is able to increase the profitability of candlestick patterns. Thirdly, by using conventional regression analysis, we find that volume per trade and turnover rates are the two main variables that can explain the profitability of candlestick patterns. Because these two variables are relevant in explaining the effect of investor sentiment in stock markets (see, e.g., Odean, 1999; Statman et al., 2006; Lai et al., 2010), our results indicate that the profitability of candlestick patterns may be based on investor sentiment.

The remainder of this paper is organized as follows. In section 2, we introduce some empirical research regarding candlestick patterns. In section 3, we show the procedures of the proposed research design. In section 4, we describe the data and the empirical analysis, while section 5 then concludes this paper.

2. Background

Logan (2008) states that candlestick charts are like road maps to the markets, which can be used to measure investors' greed and fear. One candlestick line is built based on the relationships among the opening, high, low, and closing prices. The box between the opening and closing prices is called the real body. If the closing (opening) price is higher than the opening (closing) price, the real body is white (black) which indicates excess demand (supply) in the market. The vertical line from the high (low) price to the real body is named the upper (lower) shadow (see Figure 1). Combining several consecutive lines can build various candlestick patterns, with the most common ones being composed of one to three lines.

(Insert Figure 1 about here)

Empirical research on the effectiveness of candlestick charting has produced rather mixed results. For example, Caginalp and Laurent (1998) construct a complete system to define candlestick patterns with the definition of MA_3, and find that most of the patterns can generate large profits (over 200% for a year), even when transaction costs are taken into account. Goo et al. (2007) compare the performance of various patterns and holding days by using Taiwanese data. They find that the bearish *Harami* pattern can yield an average return of 9.99% for holding ten days. Similarly, using Taiwan daily data, Shiu and Lu (2011) employ a quantile regression to test the predictive power of the two-day candlestick patterns, and also find that the bearish *Harami* pattern has genuine predictive power.

In contrast, Marshall et al. (2006) employ the bootstrap methodology and find that candlestick technical analysis cannot generate significantly positive returns when the approach of EMA_{10} is adopted. Marshall et al. (2008) use a similar approach in analyzing the Japanese stock market by dividing 100 stocks listed on the Tokyo Stock Exchange into three ten-year sub-periods, and find that candlesticks have no value for traders in this context. Horton (2009) observes nine candlestick patterns for 349 stocks listed on the S&P 500 index, and finds that the use of *Stars*, *Crows*, or *Doji* in trading individual stocks is not recommended. Moreover, Fock et al. (2005) examine the predictive power of various candlestick patterns by employing five-minute German stock indexes, and find little evidence of their profitability.

In order to provide a more comprehensive discussion about the performance of candlestick patterns, this study extends the analysis of earlier works by considering two definitions of trend and two different holding period methods. In addition, it also attempts to find out the sources of the profitability of candlesticks.

3. Research Design

As Caginalp and Laurent (1998) note, there are three crucial issues when studying candlestick charting, namely categorizing patterns, identifying trends, and calculating profits. These will all be discussed in more detail below.

3.1 Pattern Definition

Although Caginalp and Laurent (1998) present seminal work with regard to defining three-day candlestick patterns, their work includes some mistakes in the formulas used to define the patterns. Based on Nison (1991) and Morris (1995), the correct definitions of the patterns are shown as below, in which P_t^o and P_t^c refer to the opening and closing prices of day t, respectively.

(1) Three White Soldiers (TWS) after a downtrend:

$$P_i^c > P_i^o \quad \text{for } i = t+1,\ t+2,\ t+3;$$
$$P_{t+3}^c > P_{t+2}^c > P_{t+1}^c; \quad P_{t+1}^c > P_{t+2}^o > P_{t+1}^o;\ P_{t+2}^c > P_{t+3}^o > P_{t+2}^o.$$

(2) Three Inside Up (TIU) after a downtrend:

$$P_{t+1}^o > P_{t+1}^c;\ P_{t+1}^o \geq P_{t+2}^o > P_{t+1}^c;$$
$$P_{t+1}^o > P_{t+2}^c \geq P_{t+1}^c;\ P_{t+3}^c > P_{t+3}^o \text{ and } P_{t+3}^c > P_{t+1}^o.$$

(3) Three Outside Up (TOU) after a downtrend:

$$P^o_{t+1} > P^c_{t+1};\ P^c_{t+2} > P^o_{t+1} > P^c_{t+1} > P^o_{t+2};$$
$$P^c_{t+3} > P^o_{t+3} \text{ and } P^c_{t+3} > P^c_{t+2}.$$

(4) Morning Star (MS) after a downtrend:

$$P^o_{t+1} > P^c_{t+1};\ \left|P^o_{t+2} - P^c_{t+2}\right| > 0;\ P^c_{t+1} > P^c_{t+2} \text{ and } P^c_{t+1} > P^o_{t+2};$$
$$P^c_{t+3} > P^o_{t+3} \text{ and } P^c_{t+3} > P^c_{t+1} + (P^o_{t+1} - P^c_{t+1})/2.$$

(5) Three Black Crows (TBC) after an uptrend:

$$P^o_i > P^c_i \quad \text{for } i = t+1,\ t+2,\ t+3;$$
$$P^c_{t+1} > P^c_{t+2} > P^c_{t+3};\ P^o_{t+1} > P^o_{t+2} > P^c_{t+1};\ P^o_{t+2} > P^o_{t+3} > P^c_{t+2}.$$

(6) Three Inside Down (TID) after an uptrend:

$$P^c_{t+1} > P^o_{t+1};\ P^c_{t+1} > P^o_{t+2} \geq P^o_{t+1};$$
$$P^c_{t+1} \geq P^c_{t+2} > P^o_{t+1};\ P^o_{t+3} > P^c_{t+3} \text{ and } P^o_{t+1} > P^c_{t+3}.$$

(7) Three Outside Down (TOD) after an uptrend:

$$P^c_{t+1} > P^o_{t+1};\ P^o_{t+2} > P^c_{t+1} > P^o_{t+1} > P^c_{t+2};$$
$$P^o_{t+3} > P^c_{t+3} \text{ and } P^c_{t+3} < P^c_{t+2}.$$

(8) Evening Star (ES) after an uptrend:

$$P^c_{t+1} > P^o_{t+1};\ \left|P^o_{t+2} - P^c_{t+2}\right| > 0;\ P^c_{t+2} > P^c_{t+1} \text{ and } P^c_{t+2} > P^c_{t+1};$$
$$P^o_{t+3} > P^c_{t+3} \text{ and } P^c_{t+3} < P^o_{t+1} + (P^c_{t+1} - P^o_{t+1})/2.$$

In addition, these eight patterns can also be classified into two groups: patterns (1) to

(4) are bullish patterns, while patterns (5) to (8) are bearish ones. These eight patterns will be used to evaluate the profitability of candlesticks.

(Insert Figure 2 about here)

3.2 Trend Definition

For comparison purposes, we adopt two different definitions of trend to examine the performance of candlestick patterns. Following Caginalp and Laurent (1998), the approach of MA_3 is defined as below:

(1) An uptrend on day t :

$$MA_3(t-6) < MA_3(t-5) < \cdots < MA_3(t-1) < MA_3(t), \qquad (1)$$

where the three-day moving average on day t is defined by

$$MA_3(t) = \frac{1}{3}\sum_{i=t-2}^{t} P_i^c .$$

(2) A downtrend on day t:

$$MA_3(t-6) > MA_3(t-5) > \cdots > MA_3(t-1) > MA_3(t). \qquad (2)$$

Note that only when these six inequalities of $MA_3(t)$ in (1) or (2) are satisfied, is an apparent trending behavior defined.

Following Morris (1995) and Marshall et al. (2006; 2008), another definition of trend, i.e., EMA_{10}, is also employed. Let the exponential moving average on day t be defined as

$$EMA_n(t) = \alpha P_t^c + (1-\alpha)EMA_n(t-1), \tag{3}$$

where $\alpha = 2/(n+1)$ and $EMA_n(t)$ gives more weight to the most recent data, and $EMA_n(0)$ is the closing price on 4 January 1992. Given that $n = 10$ in equation (3), EMA_{10} can be calculated. The trend is classified to an uptrend if closing prices are over EMA_{10}, while a downtrend is defined if closing prices are under EMA_{10}.

3.3 Profit Calculation

In this study, we also consider two different holding periods, i.e., fixed and variable, to calculate the profit of each trade. Following Caginalp and Laurent (1998), the return rate for a fixed holding period is given by

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

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

where R_{buy} (R_{short}) denotes the return from a long (short) position. Following Lu et al. (2012), the return rate for a variable holding period is also given by

$$R_{buy} = \frac{P^o_{t_{bear}+1} - P^o_{t_{bull}+1}}{P^o_{t_{bull}+1}} \times 100\%, \tag{4}$$

$$R_{short} = \frac{-(P^o_{t_{bull}+1} - P^o_{t_{bear}+1})}{P^o_{t_{bear}+1}} \times 100\%, \tag{5}$$

where $P^o_{t_{bear}+1}$ ($P^o_{t_{bull}+1}$) denotes the opening prices at time $t_{bear}+1$ $(t_{bull}+1)$, and the date $t_{bear}+1$ $(t_{bull}+1)$ is the day after a bearish (bullish) pattern.

To be state this more clearly, we take the fixed holding period trading rule for MA_3 as an example. If, at the end of day *t*, the three-day moving average of closing prices has increased consecutively for the past seven days (i.e., from day *t-6* to day *t*), then an uptrend is identified at the end of day *t*. Next, the three-day candlestick patterns are observed for days *t+1*, *t+2* and *t+3*. A position is then opened at the start of day *t+4* and held until the end of day *t+6* (i.e., a three-day holding period). Finally, the returns from the trading positions opened following each pattern are measured and examined.

4. Data and Empirical Results

Taiwan is one of the most successful developing countries among the emerging markets (Lai et al., 2010), and the Taiwanese stock market has some unique characteristics that make it rather different from those in other Asian-Pacific nations (Comerton-Forde and Rydge, 2006). For example, the market has a number of regulations to enhance stability, such as the 7% single-day price limit (up and down 7%) on the closing price of previous trading day, short-selling restrictions on some particular stocks, and asymmetric margin systems between buyers and sellers. The Taiwan Stock Exchange (hereafter, TSE) is also an order-driven call market, and has the lowest transaction costs in the Asia-Pacific region. In addition, the majority of total trading activity on the TSE is carried out by individual investors (about 63.2% in 2012), as opposed to institutional ones, and this is also very different from other markets. According to statistics released by the World Federation of Exchanges in December 2012, the Taiwanese stock market is the world's 17th largest financial market with regard to the number of listed companies (840 firms), the 22nd largest based on market capitalization (735 USD billion), and the 15th largest by trading value (55 USD billion).[1] Because several previous studies, including Goo et al. (2007), Lu and Shiu (2012), and Lu et al. (2012), use Taiwanese data to examine the profitability of trading rules, it of interest to compare performances of various definitions of trend and holding period approaches by using Taiwanese stock prices.

It is not meaningful to discuss any trading strategy on a stock when restrictions

[1] The World Federation of Exchanges (WFE) is an association of 54 regulated exchanges from various countries (http://www.world-exchanges.org/statistics).

exist on short-selling. In the Taiwanese stock market, only the stocks listed on the Taiwan 50 component stocks data, Taiwan Mid-Cap 100, and IT index face no restrictions with regard to short-selling. As a result, the total non-overlapping stocks examined in this study only include 154 in-sample stocks. These daily stock prices from 4 January 1992 through 31 December 2012 are taken from the AREMOS databank of the Ministry of Education in Taiwan.[2] Table 1 summarizes the average returns (taking transaction costs into account) and winning rates of eight three-day patterns for the fixed holding period approach. Note that the empirical results reported here subtract all transaction costs, including a 0.3 percent trading tax, a 0.285 percent brokerage fee (although it should be noted that brokerage fees have been reduced by 50% in recent years), and a 0.1 percent bid-ask spread for a round-trip trade (Caginalp and Laurent, 1998). To test the null hypothesis that the average return is zero, the skewness adjusted *t*-test developed by Johnson (1978) is applied. In addition, the conventional binomial test is used to examine the null hypothesis that the winning rate is 50 percent, and the results are summarized in Table 1.

(Insert Table 1 about here)

As can be seen in Table 1, among the four bullish patterns only the MS one

[2] The start point of 4 January 1992 is selected because the earliest candlestick charting book in English was published until 1991, and thus proponents of technical analysis in the West would have been aware of candlestick techniques from around the start of 1992.

demonstrates significantly positive results. The average return of the MS pattern is about 1.49%, with a winning rate of 61.00%, based on the approach of MA_3, while the average return falls to 0.86%, with a winning rate of 55.15%, when the definition of EMA_{10} is considered. Similarly, among the four bearish patterns, only the ES one generates a significantly positive average return. The average return of the ES pattern is about 0.86%, with a winning rate of 59.48%, if the approach of MA_3 is taken into account, while the average return falls to 0.57%, with a winning rate of 57.94%, when the approach of EMA_{10} is adopted. The finding that the approach of MA_3 performs better than that of EMA_{10} is mainly due to the definition of a trend. According to the definition used in the MA_3 approach, the direction of the trend can be identified only when six inequalities of $MA_3(t)$ in (1) or (2) are satisfied. However, based on the approach used with EMA_{10}, the trends appear when closing prices are above or below the exponential moving average. Compared to the approach of MA_3, it is much easier to detect "trend signals" using the EMA_{10} approach. Trend analysis based on the EMA_{10} approach may increase the likelihood for noise trading, and thus generate less profit from the same simple rules. Moreover, this provides a reasonable explanation for the results obtained in Fock et al. (2005), Marshall et al. (2006), and Marshall et al. (2008), that candlestick patterns may generate negative profits when the approach of EMA_{10} is adopted.

To improve on the profitability of candlestick patterns, the variable holding period approaches discussed in equations (4) and (5) are also adopted, with the results shown in Table 2. As can be seen in this table, based on the approach of MA_3, the average return of the MS pattern is about 11.77%, with a winning rate of 54.58%, while the average return of the ES pattern is about 1.35%, with a winning rate of 63.93%. Compared to the fixed holding period approach, the variable holding period one has better performance in the sense that both MS and ES patterns generate higher average returns. Note that the average number of holding days between the MS and the next bearish pattern is 284, and that between the ES and the next bullish pattern is 321 days. These results indicate that candlestick charting can be employed in a long-term approach, and thus yield even more profits.

(Insert Table 2 about here)

To check the profitability of the candlestick patterns, we make use of subsample periods to carry out robustness checks. Following Jensen (1967), we consider a validation method where the best-performing trading rules are produced in the sample period and then a robustness check is carried out on the subsample periods. To do this, we divide the entire sample into three subsample periods, 1992-1998, 1999-2005 and 2006-2012. We then test the predictive power of the MS and ES patterns over these subsamples, with Table 3 providing a summary of the results. As can be seen in this table, both MS and ES patterns obtain significant and positive profits from all subsample periods. Moreover, the approach of MA_3 performs better than that of EMA_{10}.

(Insert Table 3 about here)

Furthermore, following Scheinkman and Xiong (2003), we regress the returns yielded by MS and ES patterns (with two different definitions of trend) on three variables, including capital (*CAP*), volume per trade (*VOL*) and turnover rates (*TURN*), and the results are summarized in Table 4. It can be seen that all the coefficients except two (*CAP* with MA_3 and EMA_{10} approaches, in panel B of Table 4) are statistically significant at the 5% level. Each of the coefficients has the anticipated sign. In addition, volume per trade and turnover rates are two main variables to explain the profitability of candlesticks, and their *t*-ratio statistics are all significant, even at 1% percent level. Because these two variables are relevant in explaining the effect of investor sentiment in stock markets (see, e.g., Odean, 1999; Statman et al., 2006; Lai et al., 2010), our result indicate that the profitability of candlestick patterns may be due to investor sentiment.

5. Conclusion

In this study, we follow earlier works and re-examine the profitability of candlestick patterns, but consider a more complete set of trending approaches and trading rules. Four interesting findings emerged from this work. Firstly, two patterns, the MS in downtrends and the ES in uptrends, yield significantly positive returns after transaction costs are considered and when using the fixed holding period approach. Secondly, the definition of trend plays a crucial role in the performance of candlesticks, with MA_3 being better than EMA_{10}. Thirdly, the performance can be improved by using the variable holding period approach. Fourthly, two investor sentiment factors, volume per trade and turnover rates, affect the profits of candlestick patterns.

The finding that candlestick charting has value for investors is in line with Caginalp and Laurent (1998), Goo et al. (2007), Lu and Shiu (2012) and Lu et al. (2012). However, to the best of our knowledge, this is the first paper that compared the effect of two definitions of trend and attempted to find the cause of the profitability of candlesticks. To further understand the supply and demand situation of a particular market, behavioral finance theories could be considered into future research.

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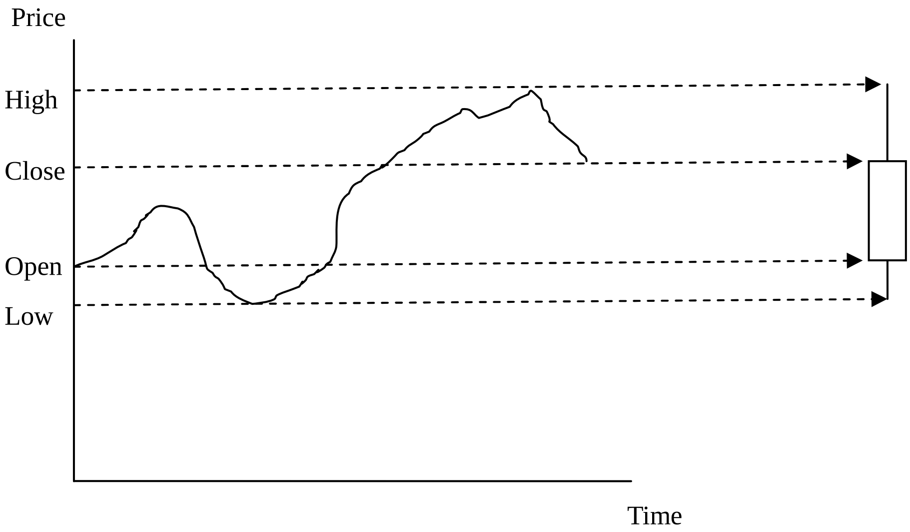
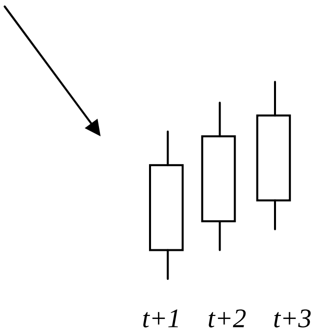
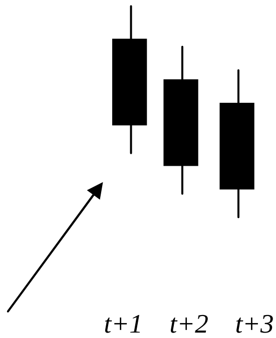
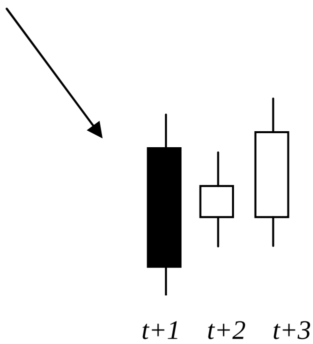
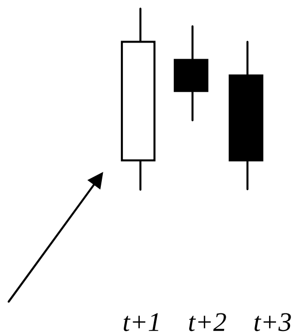


Figure 1: Candlestick bullish single line.

Bullish Patterns	**Bearish Patterns**
Three White Soldiers (TWS) 	*Three Black Crows (TBC)* 
Three Inside Up (TIU) 	*Three Inside Down (TID)* 

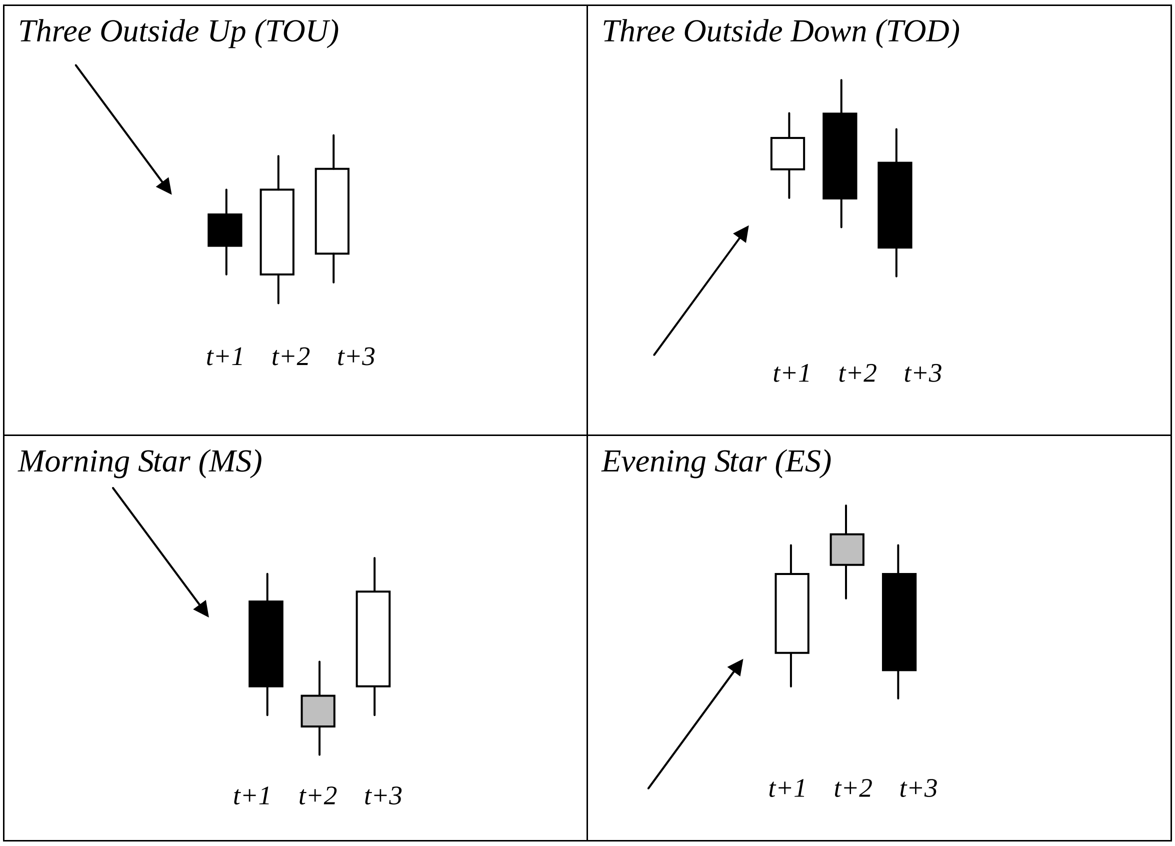


Figure 2: Categories for three-day candlestick patterns.

Table 1 Summary of the fixed holding period approach

Patterns	MA_3			EMA_{10}		
	No.	Returns	Win%	No.	Returns	Win%
Panel A: Bullish patterns						
TWS	209	-0.15*(<0.65)	39.23* [<0.01]	892	-0.59* (<0.01)	36.66* [<0.01]
TIU	418	-0.90* (<0.01)	32.06* [<0.01]	2786	-0.39* (<0.01)	40.13* [<0.01]
TOU	370	-0.11*(<0.63)	41.35* [<0.01]	2003	-0.51* (<0.01)	38.59* [<0.01]
MS	1823	1.49* (<0.01)	61.00* [<0.01]	12652	0.86* (<0.01)	55.15* [<0.01]
Panel B: Bearish patterns						
TBC	648	-1.06* (<0.01)	36.57* [<0.01]	3847	-0.77* (<0.01)	39.59* [<0.01]
TID	162	-0.62* (<0.04)	40.12* [<0.01]	1402	-0.30* (<0.01)	43.37* [<0.01]
TOD	695	-0.97* (<0.01)	39.71* [<0.01]	5514	-0.75* (<0.01)	39.19* [<0.01]
ES	1905	0.86* (<0.01)	59.48* [<0.01]	18515	0.57* (<0.01)	57.94* [<0.01]

Note: The numbers in parentheses and brackets represent *p*-values of skewness adjusted *t*-test and binomial test. * indicates statistical significance at the 5% level. The term No. denotes the number of days in each pattern.

Table 2 Summary of the variable holding period approach

Patterns	No.	Holding days	Returns%	Std.	Skewness adjusted *t*-test *p*-value	Winning rate%	Binomial test *p*-value
Panel A: Bullish patterns							
TWS	84	257	20.09*	0.52	<0.01	63.10*	0.02
TIU	283	241	3.41*	0.48	0.22	50.53*	0.91
TOU	184	287	16.82*	0.76	<0.01	53.80*	0.34
MS	1387	284	11.77*	0.60	<0.01	54.58*	<0.01
Panel B: Bearish patterns							
TBC	276	335	2.06*	0.47	0.48	67.75*	<0.01
TID	114	330	-0.49*	0.64	0.90	60.53*	0.03
TOD	324	319	2.93*	0.44	0.24	64.51*	<0.01
ES	1170	321	1.35*	0.03	0.39	63.93*	<0.01

Note: Holding days refers to the average days from entering to exiting the market. * indicates statistical significance at the 5% level. The terms No. denotes the number of days and the term Std. is the standard deviation in each patter.

Table 3 Sub-sample Results

Patterns	MA$_3$			EMA$_{10}$		
	No.	Returns	Win%	No.	Returns	Win%
Panel A: MS patterns						
1992-1998	646	1.35* (<0.01)	61.92* [<0.01]	2096	0.74* (<0.01)	54.96* [<0.01]
1999-2005	665	1.83* (<0.01)	61.05* [<0.01]	4394	1.11* (<0.01)	56.58* [<0.01]
2006-2012	512	1.23* (<0.01)	59.77* [<0.01]	4444	0.73* (<0.01)	53.89* [<0.01]
Panel B: ES patterns						
1992-1998	565	0.89* (<0.01)	63.72* [<0.01]	6511	0.55* (<0.01)	59.47* [<0.01]
1999-2005	554	1.43* (<0.01)	64.08* [<0.01]	5665	0.78* (<0.01)	59.68* [<0.01]
2006-2012	786	0.44* (<0.01)	53.18* [<0.01]	6339	0.40* (<0.01)	54.80* [<0.01]

Note: The numbers in parentheses and brackets represent *p*-values of skewness adjusted *t*-test and binomial test. * indicates statistical significance at the 5% level. The term No. denotes the number of days in each sub-sample

Table 4 Regression Results

	MA_3			EMA_{10}		
Variable	Coefficient	Std. error	*t*-ratio	Coefficient	Std. error	*t*-ratio
Panel A: MS pattern						
CAP	-0.0013*	0.0005	-2.5837	-0.0005*	0.0001	-3.2303
VOL	-0.1142*	0.0347	3.2944	-0.1496*	0.0390	3.8323
TURN	-0.3755*	0.1354	2.7743	-0.0598*	0.0109	5.4759
Panel B: ES pattern						
CAP	-0.0004	0.0004	-1.1274	-0.0001*	0.0001	-0.4816
VOL	-0.1943*	0.0382	5.0912	-0.2147*	0.0140	15.3318
TURN	-0.1193*	0.0367	3.2524	-0.0434*	0.0093	4.6470

Note: The numbers in parentheses represent *p*-values of the regressors. * indicates statistical significance at the 5% level.