Market Timing with Candlestick Technical Analysis

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Abstract

We investigate the profitability of the quantitative market timing technique of candlestick technical analysis in the U.S. equity market. Despite being used for centuries in Japan and now having a wide following amongst market practitioners globally, there is little research documenting its profitability or otherwise. We find that these strategies are not generally profitable when applied to large U.S. stocks. Basing trading decisions solely on these techniques does not seem sensible but we cannot rule out the possibility that they compliment some other market timing techniques.

JEL Classification: *G12, G14*

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1. Introduction

Debate on the degree to which asset returns can be predicted has continued in Western finance communities for over fifty years. The importance of this debate to the global economy has resulted in a huge amount of research energy being devoted to this area. The academic and practitioner communities have historically been divided on this issue. Academics have traditionally believed that returns are not predictable because if they were, rational market participants would soon learn of this predictability and trade it away. In contrast, a large portion of the investment industry is based on the premise that value can be added by market timing techniques. Academics now generally accept that returns do have some predictability; however, most maintain that it is not possible to profit from this.

The worth of technical analysis is critical to the return predictability debate. Technical analysis involves using past price movements to make investment decisions. If technical analysis is shown to have value then there is evidence that it is indeed possible to profit from return predictability. Alternatively, if technical analysis is shown to be worthless then the rationality of market participants who devote a large amount of resource to its pursuit needs to be questioned. The first mention of technical analysis in the West appears to be by Charles Dow in the late 1800s. However, at this time Dow did not know that technical analysis principles, now known as *candlestick technical analysis*, were being used in Japan and had been for at least one hundred years.

Robust tests of technical analysis have focused on trading rules, such as moving average, support and resistance, and trading range break-out rules, that have their origins in the Western world. The majority of this literature shows that technical analysis does not have value once transaction costs and risk adjustment are taken into account (e.g. Bessimbinder and Chan, 1998; Ito, 1999). A smaller strand of literature shows that the application of technical analysis does result in excess returns (e.g. Ratner and Leal, 1999). This paper considers the profitability of candlestick technical analysis. Candlestick technical analysis was introduced to the Western world by Steve Nison in 1991 in a book titled *Japanese Candlestick Charting Techniques: A Contemporary Guide to the Ancient Investment Techniques of the Far East*.

Candlestick trading rules rely on one to three days of historical data to generate a signal. Positions are generally held for up to 10 days. This short-term focus makes them very popular with market participants, who favour technical analysis for short-term horizons.

Nison (2004, p. 22) comments "since its introduction to the Western world candlestick technical analysis has become ubiquitous, available in almost every software and online charting package."

According to Pring (2002), candlestick technical analysis dates back to the mid 1700s when a wealthy Japanese businessman, Munehisa Homma, applied these principles at his local rice exchange in Sakata. Homma became a very famous and wealthy rice trader. Candlestick technical analysis involves the consideration of the relationship between open, high, low, and close prices. These four prices are displayed as objects that look like candles as shown in Figure 1 (when the close is above (below) the open the candle "body" is white (black). All descriptions of candlestick technical analysis patterns and the theory behind them in this paper are derived from the practitioner books: Bigalow (2002), Fischer and Fischer (2003), Morris (1995), Nison (1991, 1994), Pring (2002) and Wagner and Matheny (1993). The interested reader should refer to these books for more detailed descriptions.

[Insert Figure 1 About Here]

A daily candlestick is a graphical representation of the day's open, high, low, and close prices. Daily candlesticks are commonly referred to as "single lines". Some single lines are said to have forecasting power in their own right while others do not. Certain combinations of single lines over successive days create continuation and reversal patterns. Continuation patterns indicate the prevailing trend will continue, while reversal patterns suggest there will be a change in trend.

2. Data and Methodology

Data choice is very important to tests of technical analysis. Firstly, it is important that the chosen data are able to be traded in reality in the same manner in which they are tested. For instance, the use of index data in technical analysis research is a dubious approach if the index is unable to be traded in its own right in reality. Secondly, it is important that the data are from instruments of sufficient liquidity to enable market participants to make meaningful amounts of money. This liquidity aspect is also important to provide a fair test of technical analysis. Proponents of technical analysis claim that it is a measure of mass market psychology. It is therefore less useful for trading thinly traded stocks whose prices are more susceptible to being moved by as little as one market participant. Finally, it is important that theories are tested on data that are different from those on which they were developed. This ensures that the theories do not simply hold on the one data set.

In this paper, the profitability of candlestick technical analysis is tested using individual stock data for those companies that were included in the Dow Jones Industrial Index (DJIA) during the 1/1/1992 – 31/12/2002 period. Price data are sourced from Reuters and dividend data are sourced from CRSP. This data set was chosen to address the data issues outlined above and to ensure that data snooping bias is minimised. Data snooping bias can occur if the data set that is used to develop a theory is used to test and verify that same theory. In this research, the use of U.S. stock data to test candlestick technical analysis, which were developed using Japanese rice data, is most clearly an out of sample test.

We now turn our attention to a description of candlestick single lines and patterns. A single line, such as the Long White Candle displayed in Figure 2, is formed within one trading day.

[Insert Figure 2 About Here]

A Long White Candle has a close well above the open towards the high of the day. This is said to indicate positive sentiment and therefore suggest that the price can be expected to rise in the future. As stated in Marshall, Young, and Rose (2006), single lines over successive days can form continuation and reversal patterns. Continuation (reversal) patterns indicate that the prevailing trend will continue (change). There are bullish and bearish varieties of all single lines and most continuation and reversal patterns. Bullish (bearish) single lines and patterns are said to indicate future price increases (decreases). To determine whether a continuation or reversal pattern has strong forecasting power, proponents of candlestick technical analysis, such as Nison (1994) and Morris (1995), developed a system of combining the two or three individual single lines that make up the pattern to form an overall single line for the two- or three-day period (Marshall, Young, and Rose, 2006). We follow the approach outlined by Marshall, Young, and Rose (2006) and arrive at a universe of 14 single lines and 14 reversal patterns to test.

An example of a bullish reversal pattern is the Hammer, which is displayed in Figure 3.

[Insert Figure 3 About Here]

The Hammer involves a decline in price to a new intra-day low. A rally in prices then occurs resulting in a close above the open. Prices continue to increase the next day indicating a reversal of trend has occurred. Nison (1991, p. 29) stated that the lower shadow should be twice the height of the real body and it should have no, or a very short, upper shadow. The interested reader should refer to Marshall, Young, and Rose (2006) and the books mentioned on page 3 for more discussion on different single lines and reversal patterns.

The profitability of candlestick trading strategies is tested using *t*-statistics and the bootstrapping methodology. Candlestick technical analysis has a short-term focus. We investigate holding periods of two, five, and ten days and find the results are very similar so we only present our ten day results to conserve space. The methodology description is therefore based on a ten-day holding period. The approach is to firstly investigate whether there is any statistical significance to the profits from following candlestick signals.

First we consider the *t*-test methodology, which involves comparing the returns following a technical analysis signal to returns when there is no signal. If returns following a candlestick buy (sell) signal are statistically significantly greater (less) than the unconditional return a candlestick trading rule has forecasting power. Returns were measured on a daily basis as the log difference of price relatives. The *t*-statistics for the buy (sell) signals versus no signals are:

$$\frac{\mu_{b(s)} - \mu}{(\sigma^2_{b(s)} / N_{b(s)} + \sigma^2 / N \ )^{1/2}} \qquad (1)$$

where $\mu_{b(s)}$ and $N_{b(s)}$ are the mean return following a buy (sell) signal for the ten day holding period and the number of signals for buys (sells). μ and N are the unconditional mean and number of observations. $\sigma^2_{b(s)}$ is the variance of returns following a buy (sell) signal and σ^2 is the variance for the entire sample.

Since this *t*-test methodology is dependent on several assumptions that do not generally hold for financial data (see Brock et al. (1992)), a bootstrapping methodology was also applied. This methodology has several advantages. Firstly, unlike *t*-statistics bootstrapping can accommodate well known characteristics of stock return data such as skewness and leptokurtosis. The bootstrap methodology has the added advantage of being able to be used to determine the riskiness of the different candlestick rules.

The bootstrap methodology requires a choice of null model to fit the data. To ensure consistency with the previous technical analysis literature (e.g. Brock et al. (1992)) we consider random walk, AR(1), GARCH-M and EGARCH null models. Our results are very consistent across null models so we present our EGARCH results in this paper. The EGARCH model is similar to the GARCH-M model in that both accommodate volatility in the return generating process. However, it has two important differences from the GARCH-M model. Firstly, the log of the conditional variance follows an autoregressive process. Secondly, it allows previous returns to affect future volatility differently depending on their sign.

$$r_t = \alpha + \gamma r_{t-1} + \beta \varepsilon_{t-1} + \varepsilon_t \qquad (2a)$$

$$\log \sigma_t^2 = \kappa + G \log \sigma_{t-1}^2 + A_j \left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{2/\pi} \right] + L \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right) \qquad (2b)$$

$$\varepsilon_t = \sigma_t z_t \qquad z_t \sim N(0,1) \qquad (2c)$$

In accordance with Brock et al. (1992), the residuals of the EGARCH models are standardised using estimated standard deviations for the error process. The standardised residuals are then redrawn with replacement to form a scrambled residuals series. These series and the estimated parameters, are used to generate a new representative close return series. These returns are then expontiated to form new close price series for each stock. These scrambled series have the same drift in prices, the same volatility, and the same unconditional distribution but the returns are independent and identically distributed. (Marshall, Young, and Rose, 2006).

As outlined in Marshall, Young, and Rose (2006), once a randomly generated close series has been formed vectors of the original (high – close)/close and (close-low)/close percentage differences are created. The next step involves taking a random sample from these percentage difference vectors. We then add (subtract) these high-close (close-low) percentage differences are added to (from) the simulated close price to form simulated high and low prices. A similar process is used to generate simulated open prices. We build in a check to ensure that the resampled open price is never higher than the high nor lower than the low. If this occurs the close-open percentage differences are resampled again. This process outlined above is replicated 500 times for each stock so there are 500 simulated sets of open, high, low and close series for each stock in the sample for each null model.

As described in Brock et al. (1992), the proportion of times that a trading rule produces more profit on the bootstrapped series than on the original series following a signal is a simulated p-value for the null hypothesis that the trading rule has no value. For instance a bullish candlestick has statistically significant forecasting power at the 1% level if the simulated p-value is less than 0.01. Put another way, more profit should be produced on the random series than the original less than 1% of the time. For a bearish candlestick to have forecasting power at the 1% level the simulated p-value should be more than 0.99. In other words, there should be more profit on the random series than on the original more than 99% of the time.

3. Results

Most research follows Brock et al. (1992) and assumes that a technical trader could buy a stock at the close price on the same day that a signal is generated. In reality, this is very difficult as the close price of the stock is what determines whether a trading signal will be generated. A technical analyst following this approach would have to firstly feed estimates of the close price into his/her trading system to see if they generated a signal. If one did s/he would then need to submit a "market at close" order. At this point s/he could not be sure that the actual close price would be sufficiently similar to the estimated close price to have generated the signal so there is a risk of acting on an invalid signal.

In this paper we present results based on the assumption that a trade is entered at close on the day after a signal. We conduct sensitivity analysis around this by considering entering at the open price on the day following the signal but our results are little different. We follow Morris (1995) and use a ten-day exponential moving average to determine the prior trend for bullish and bearish reversal patterns. We verify that our results are robust to changes in the length of this.

[Insert Table 1 About Here]

The *t*-test results are displayed in Table 1. Bullish single lines and patterns are presented in Panels A and B of Table 1. N(Buy) is the number of buy signals in the data. This ranges from 17 for the Three Inside Up pattern to 2,947 Long White single line. The tests are based around a ten-day holding period, but daily returns are used in the statistical tests so that their power is increased. This means that the number of signals needs to be multiplied by ten to arrive at the number of returns used in the statistical tests. For instance, there are 170 daily returns associated with the Three Inside Up pattern.

The column Buy>0 reports the proportion of returns following a buy signal that are greater than zero. The returns following all the bullish single lines are greater than zero less than fifty percent of the time. This may indicate a poorly performing rule, however it is not conclusive as it is possible that a rule that is correct less than fifty percent of the time generates profits that are a lot bigger than the losses making it profitable overall. The only bullish reversal pattern to yield returns greater than zero more than fifty percent of the time is the Bullish Harami pattern.

The mean returns conditional on bullish single line signals are all positive with the exception of the Opening White Marubozu and Dragonfly Doji. Despite this, none of the bullish single lines yield statistically significant profits at the 5% level. Rather, all of the *t*-statistics except those for the White Paper Umbrella are negative. This indicates that the mean return conditional on all the non- White Paper Umbrella bullish single line signals are lower than the unconditional mean return. The returns following Opening White Marubozu lines are negative and statistically significant at the 1% level. This is exactly the opposite to what candlestick technical analysis theory suggests. Rather than indicating positive future returns, there is evidence that this single line indicates negative future returns. The *t*-statistics for the Hammer, Bullish Engulfing, Bullish Harami, and Three Inside Up bullish reversal patterns are positive, indicating that the conditional returns are greater than the unconditional returns. However, none of these are statistically significant.

The results from bearish single lines and patterns are presented in Panels C and D of Table 1. The number of bearish single lines and patterns is similar to the number of their bullish counterparts. The returns following all bearish single lines are greater than zero less than fifty percent of the time, which means that they are less than zero more than fifty percent of the time. This is what one would expect for a bearish candlestick. The bearish reversal patterns are also greater than zero less than fifty percent of the time, with the exception of the Three Outside Down pattern.

Other than the Three Inside Down pattern, the means of the bearish single lines and reversal patterns are all positive. The Long Black and Black Marubozu conditional minus unconditional mean are statistically significant at the 5% level. This suggests that, contrary to candlestick theory, these bearish lines indicate higher than average returns over the next ten days. The *t*-statistics for the Bearish Harami and Three Inside Down bearish reversal patterns are negative (as expected), but none of these are statistically significant.

[Insert Table 2 About Here]

The bootstrap results are displayed in Table 2. The p-values refer to the proportion of the 500 simulated bootstrapped series that have higher average returns and standard deviations following a buy (sell) signal from a bullish (bearish) rule than the original series. These numbers can be thought of as simulated p-values. For the bullish candlestick buy returns a value of zero indicates that none of the bootstrapped series have a return following a buy signal that is larger than that on the original series. This indicates that the rule has significant power. For a bearish candlestick, a value of one indicates that all of the bootstrapped series have returns that are larger than those on the original series following a sell signal. Again, this indicates that the rule has significant power. For a rule to have statistically significant forecasting power at the 1% level, consistent with candlestick theory, a simulated p-value has to be less than 0.01 (greater than 0.99) for bullish (bearish) rules.

The buy proportions for the single lines are all between 0.35 and 0.70, which indicates that none of these candlesticks generate conditional returns that are statistically significantly different from the unconditional returns. If a trading rule has statistically significantly different returns, an obvious question to ask is whether or not this difference is due to additional risk being undertaken. The σ_b column displays the proportion of times that the standard deviation of returns following a buy signal is greater on the bootstrapped series than on the original series. If a trading rule is in the market in more risky times, σ_b will be close to one. The results in Panel A indicate that there is no clear relationship in the standard deviation proportions for the bullish single lines. Some proportions are closer to zero while others are closer to one. None are statistically significant at the 5% level.

From the Panel B results it is evident that the returns following bullish reversal patterns are also not statistically significant, indicating that bullish reversal patterns have no forecasting power. Similar to the bullish single lines, there is no clear pattern in the standard deviations. Returns on the original series are sometimes more volatile than 50% of the bootstrapped series, and sometimes less volatile.

Returns are greater on the bootstrap series than on the original series less than fifty percent of the time for all bearish single lines (except the White Shooting Star). This is the opposite to what one would expect for bearish rules, but is broadly consistent with the *t*-statistic results which show that in some instances bearish single lines forecast negative rather than positive future returns. The sell p-values from the bearish reversal patterns are also less than 0.5, with the exception of the Dark Cloud Cover, Bearish Harami, and Three Inside Down patterns. The standard deviation p-values for the bearish single lines and reversal patterns show no clear trend.

The fact that none of the bootstrap results are statistically significant indicates that the t-statistic results, which showed statistical significance in five cases, may be influenced by one of the t-statistic assumptions being violated. The summary statistics in Table 2 show that the return series are not normally distributed (as required for the t-test to be accurate), but rather display characteristics of negative skewness and leptokurtosis.

The final four columns in Tables 2 contain the means and standard deviations for the bootstrapped and original series. Bootstrap Buy and σ_b are the mean buy return and standard deviation of buy returns across the 500 bootstrapped series respectively. These are calculated as an average of the 500 series across the 35 stocks. Dow Buy and σ_b are the average buy return and standard deviation of buy returns across the original series for each of the 35 stocks.

A comparison with the p-value results show that it is usually the situation that the size of the bootstrap p-value for the mean or standard deviation is indicative of the relative size of the means or standard deviations for the bootstrap and the original series. For instance, if the buy proportion for a bullish rule is greater than 0.5, indicating that the bootstrap return is greater than the original return in excess of 50% of the time, then the bootstrap mean is in fact greater than the original mean. An example of this is the Long White candle which has a p-value of 0.6309 and mean return of 0.0001 and 0.0000 on the bootstrap and original series respectively. This is not always the case though. It is possible that the bootstrap return is greater than the original return over 50% of the time but that the remaining bootstrap returns are very small, resulting in an overall bootstrap mean that is less than the original mean. An example of this is the Piercing Line which has a bootstrap p-value of 0.4656 and means of 0.0000 and -0.0002 on the bootstrapped and original series respectively. The bearish single line and pattern average sell returns and standard deviation are very similar to the bullish results. The size of the bootstrap proportion is usually indicative of the relative size of the means and standard deviations for the bootstrapped and original series.

Candlestick signals are reasonably rare and their forecasting power is only a short-term phenomenon (Morris, 1995) so it is not appropriate to consider their daily returns on an annual basis. Large daily returns are not able to be earned over a sustained period of time. More specifically, a particular candlestick pattern might produce an average daily return of 1% over a ten-day holding period in a particular stock, but if the pattern signals only one entry per year on average it is not realistic to conclude that it produces an annual return in excess of 250% (obtained by annualising the daily returns). There is a small chance that the results are not consistent across the entire eleven year period of this study. This is investigated by dividing the data into two equal sub-samples and running the tests on each of these. The results are very consistent across these sub-samples.

In summary, we find some weak evidence of negative return predictability in our *t*-statistic results. Candlestick lines and patterns supposed to predict larger than normal positive returns sometimes actually predict smaller than normal returns and vice versa. However, the results generated by the superior bootstrap methodology show no evidence that candlestick lines and patterns generate predictability in prices.

4. Conclusions

The worth of marketing timing techniques such as technical analysis has been a long standing debate with the finance community over the last fifty years. Academics have historically dismissed technical analysis due to it being in conflict with the efficient market hypothesis, but the continued use of these techniques by practitioners and recent studies which have shown technical trading rules can be applied profitably has resulted in more researchers focusing on this area in recent times.

We contribute to this literature by examining the profitability of candlestick technical analysis in the U.S. equity market. These techniques, which have been successfully applied to rice trading in Japan from at least the 1700s, have received relatively little research attention. Candlestick technical analysis involves the consideration of the relationship between open, high, low, and close prices. These four prices are displayed as objects that resemble candles. Candlestick trading rules rely on one to three days of historical data to generate a signal. Positions are generally held for up to 10 days. This short-term focus makes them very popular with market participants who favour technical analysis for short-term horizons. Nison (2004, p. 22) comments "since its introduction to the Western world candlestick technical analysis has become ubiquitous, available in almost every software and online charting package."

Using robust statistical techniques, we find that candlestick trading rules are not profitable when applied to DJIA component stocks over 1/1/1992 – 31/12/2002 period. Neither bullish or bearish candlestick single lines or patterns provide market timing signals that are any better than what would be expected by chance. Basing ones trading decisions solely on these techniques does not seem sensible but we cannot rule out the possibility that they compliment some other market timing techniques.

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Table 1: T-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	2947	0.4754	0.0001	-1.933
White Marubozu	642	0.4586	0.0003	-0.307
Closing White Marubozu	1565	0.4711	0.0003	-0.332
Opening White Marubozu	1611	0.4681	-0.0001	-2.710**
Dragonfly Doji	270	0.4433	-0.0001	-1.556
White Paper Umbrella	567	0.4750	0.0005	0.682
Black Paper Umbrella	727	0.4708	0.0003	-0.278
Panel B: Bullish Reversal Patterns				
Hammer	57	0.4947	0.0007	0.377
Bullish Engulfing	252	0.4869	0.0007	0.831
Piercing Line	138	0.4812	-0.0003	-1.034
Bullish Harami	115	0.5026	0.0008	0.758
Three Inside Up	17	0.4588	0.0006	0.155
Three Outside Up	56	0.4732	-0.0003	-0.744
Tweezer Bottom	354	0.4636	0.0001	-0.658
Candlestick	N(Sell)	Sell>0	Mean	*T*-Stat
Panel C: Bearish Single Lines				
Long Black	2661	0.4883	0.0007	2.105*
Black Marubozu	557	0.4783	0.0009	2.083*
Closing Black Marubozu	1022	0.4833	0.0006	1.338
Opening Black Marubozu	1737	0.4811	0.0005	1.220
Gravestone Doji	191	0.4597	0.0008	1.071
White Shooting Star	520	0.4808	0.0004	0.233
Black Shooting Star	465	0.4813	0.0005	0.711
Panel D: Bearish Reversal Patterns				
Hanging Man	84	0.4786	0.0006	0.384
Bearish Engulfing	289	0.4965	0.0009	1.645
Dark Cloud Cover	117	0.4872	0.0004	0.072
Bearish Harami	396	0.4699	0.0000	-1.102
Three Inside Down	34	0.4353	-0.0011	-1.324
Three Outside Down	36	0.5111	0.0017	1.342
Tweezer Top	407	0.4747	0.0007	1.305

**statistically significant at the 1% level, *statistically significant at the 5% level

Table 2: Bootstrap Results

Candlestick	p-Values Buy	p-Values σ_b	Bootstrap Buy	Bootstrap σ_b	Dow Buy	Dow σ_b
Panel A: Bullish Single Lines						
Long White	0.6309	0.6309	0.0001	0.0105	0.0000	0.0103
White Marubozu	0.5464	0.5464	0.0002	0.0101	0.0000	0.0087
Closing White Marubozu	0.5463	0.5463	0.0002	0.0104	0.0000	0.0097
Opening White Marubozu	0.6614	0.6614	0.0001	0.0104	-0.0002	0.0101
Dragonfly Doji	0.5438	0.5438	0.0002	0.0096	0.0000	0.0075
White Paper Umbrella	0.4492	0.4492	0.0002	0.0097	0.0003	0.0085
Black Paper Umbrella	0.5175	0.5175	0.0002	0.0099	-0.0001	0.0090
Panel B: Bullish Reversal Patterns						
Hammer	0.4497	0.4497	0.0001	0.0077	0.0004	0.0076
Bullish Engulfing	0.4243	0.4243	0.0000	0.0090	0.0003	0.0101
Piercing Line	0.4656	0.5656	0.0000	0.0089	-0.0002	0.0105
Bullish Harami	0.4550	0.4550	0.0001	0.0085	0.0005	0.0105
Three Inside Up	0.5030	0.5030	0.0003	0.0083	0.0003	0.0084
Three Outside Up	0.5083	0.5083	0.0002	0.0080	-0.0001	0.0092
Tweezer Bottom	0.4901	0.4901	0.0001	0.0081	0.0003	0.0098

Candlestick	p-Values Sell	p-Values σ_s	Bootstrap Sell	Bootstrap σ_s	Dow Sell	Dow σ_s
Panel C: Bearish Single Lines						
Long Black	0.3487	0.2407	0.0001	0.0104	0.0003	0.0108
Black Marubozu	0.3689	0.5302	0.0002	0.0102	0.0002	0.0098
Closing Black Marubozu	0.4307	0.3890	0.0001	0.0105	0.0005	0.0103
Opening Black Marubozu	0.4203	0.2634	0.0001	0.0104	0.0002	0.0108
Gravestone Doji	0.4224	0.6967	0.0002	0.0098	0.0005	0.0076
White Shooting Star	0.5308	0.5500	0.0002	0.0100	-0.0003	0.0098
Black Shooting Star	0.4551	0.6798	0.0002	0.0102	-0.0002	0.0092
Panel D: Bearish Reversal Patterns						
Hanging Man	0.4923	0.5945	0.0003	0.0100	0.0005	0.0083
Bearish Engulfing	0.4721	0.5410	0.0003	0.0104	0.0004	0.0095
Dark Cloud Cover	0.5194	0.5298	0.0003	0.0103	0.0001	0.0092
Bearish Harami	0.5881	0.5470	0.0003	0.0105	0.0000	0.0097
Three Inside Down	0.5703	0.4444	0.0003	0.0096	-0.0001	0.0097
Three Outside Down	0.4371	0.4943	0.0002	0.0092	0.0010	0.0096
Tweezer Top	0.4981	0.6127	0.0003	0.0097	0.0002	0.0083

Figure 1. Open, High, Low and Close Prices Displayed as Candles

When the close is above (below) the open the candle “body” is white (black).

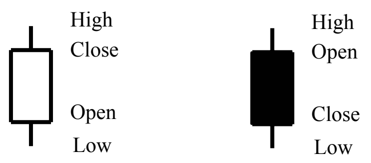

Figure 2. Long White Candle

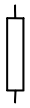

Figure 3. Hammer