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The Predictive Power of Candlestick Patterns

An Empirical Test of Technical Indicators on the Swedish Stock Market Using GARCH-M and Bootstrapping

Author:

Max Jönsson

Advisor:

Dag Rydorff

Sammanfattning

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Författare: Max Jönsson

Handledare: Dag Rydorff

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Syfte: Studiens syfte är att undersöka prognosförmåga och lönsamhet av en handelsstrategi som förlitar sig på tekniska indikatorer baserade på candlestick mönster. Avsikten är att testa den kortsiktiga lönsamheten av de handelssignaler som generars av handelsstrategin för potentiella daytraders eller andra kortsiktiga spekulanter

Metod: För att testa lönsamhet och prognosförmåga används tre statistiska tester, en med inriktning uteslutande på prognosförmåga och två med fokus på lönsamhet. Datan som används består av öppnings-, hög-, låg- och stängningskurser för 29 aktier som ingår i den svenska NASDAQ OMXS30-index. Den testade perioden löper från 19/10 2007 till 30/12 2015.

Resultat Resultaten presenterar en övergripande skeptisk syn på lönsamhet och prognosförnåga för candlestick mönster. Studien visar att prognosförmågan och lönsamheten är låg för både enskilda aktier och alla aktier tillsammans.

Slutsats: Studien finner föga värde i candlestick mönster som handelsindikatorer över korta innehavsperioder. Resultaten ger ytterligare stöd för teorin om svag effektivitet samt för random walk modellen på den svenska aktiemarknaden.

Abstract

Title: The Predictive Power of Candlestick Patterns

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Keywords: Candlestick patterns, technical analysis, bootstrap, ARCH, GARCH-M, efficient market hypothesis, random walk model, OMXS30

Research Objective: The study's objective is to examine the predictive power and the profitability of technical analysis indicators based on candlesticks patterns. The intent is to test the short term profitability of the indicators for potential day traders or other short term investors.

Methodology: To test the profitability and predictive power, three statistical tests are applied, one focusing exclusively on predictive power and two focusing on profitability. The data used is comprised of the open, high, low and closing prices of 29 stocks included in the Swedish NASDAQ OMXS30 index. The period tested starts 19 October 2007 and ends 30 December 2015.

Empirical Results: The results presents an overall negative view of the profitably and predictive power of candlestick charting analysis. The predictive power and profitability is shown to be poor for both individual stocks and all stock combined.

Conclusions: The study finds little value in candlestick patterns as buy/short indicators over short holding periods. The results lend additional support that the theory that the Swedish stock market is weakly efficient and that the random walk model is in effect.

Acknowledgements

While I am credited as the author of this paper, I have by no means been its sole contributor. I wish to express my thanks to family and friends who have assisted me throughout this project. Without your help the paper would be riddled with spelling errors and nonsensical sentences. I also want to extend sincerest thanks to my advisor, Dag Rydoff, PhD student at the Department of Economics Lund, for his expert guidance and invaluable advice.

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1. Introduction

1.1 Background

The goal of an investor is generally to attain the maximum return on investment. When it comes to investing in stocks there are two generally accepted approaches, the fundamental analysis approach which focuses on all publicly available information and the technical analysis approach which studies historical price information. Which of these two are most effective, depends largely on what the market looks like in terms of efficiency (Elton et al. 2009).

For decades the issue of market efficiency has been discussed in academia, the debate has been fueled by a series of successive studies lending either support for or against the theory (Sewell 2011). The efficient market hypothesis was first coined by Roberts (1967) and then later comprehensibly studied and presented by Fama (1970).

The theory of efficient markets states that if prices reflect all the available information and everyone has access to the same information, then studying past prices as a means to get ahead of other investors is futile (Fama 1970). In an inefficient market however, it is possible for market actors to predict future prices by studying historical price movements of stocks or other financial assets. By generating trading signals based on these predictions, an investor can attain excess returns in an inefficient market, this process is known as technical analysis (Raymond 2012).

Japanese candlestick pattern analysis is one of the more popular and certainly one of the easier to use technical analysis methods available today. It is also the oldest, having been utilized as early as the 1700s by traders in the Japanese rice futures market (Nison 1991). The methodology is however, still fairly new to the west, only being popularized during the 1990s (Marshall et al. 2006)

Candlestick pattern analysis uses the open, high, low and closing prices (OHLC) for any given day or succession of days, to assess the psychology of the market and predict how market actors will react in the future (Nison 1991). Candlestick analysis then generates buy, sell and short signals based on these predictions, which in theory allows the investor to attain excess returns. The focus on the open, high, low, and closing prices separates candlestick patterns from most other technical analysis tools which focus primarily on the closing price.

This study tests the profitability of technical analysis indicators which are based on candlestick charting. Moreover, the trend reversal ability of these technical analysis indicators is tested. The study uses a total of 8 candlestick patterns as buy and short signals, when a signal is identified, a short or long position is entered into and then held for a period of days. The focus lies on the short term since according to Morris (1995), candlestick patterns only retain informational value for 7 to 10 days.

1.2 Research Objectives

The main objective of the study is to statistically examine the predictive power and profitability of candlestick charting analysis. In essence to determine if candlestick patterns can be used to attain significant returns or predict future price trends. Thereby the objective is to contribute to the existing research on technical analysis by testing if the Swedish stock market over the period from 2007 to 2015 is weakly efficient or not.

1.3 Research Problem

The Swedish stock market continues to grow, the stock value of held by Swedish investors 2015 was 724 billion SEK (SCB 2016), which is a significant increase compared to the 363 billion SEK of 2005 (SCB 2006). The daily turnover has similarly increased from 14.5 billion SEK in 2005 (NASDAQ 2006) to 19.2 billion SEK in 2016 (NASDAQ A 2016). The number of transaction has also increased from 24.9 million in 2007 to 64.7 million in 2015 (NASDAQ B, 2016). The increase in trade and value is largely attributable to the digitalization of the market that has occurred since the early 2000s (Myreteg 2008). With the increase in trade and market participants, the interest for trading information and strategies can also be expected to have increased. Consequently, there are today many individuals trying to cash in, selling their strategy as the one “guaranteed” to make any investor rich. By performing a scientific study of one strategy, the hope is to give potential investors further insight into what works and what does not in terms of technical analysis.

1.4 Previous Studies

Following the introduction and popularization of candlestick charting analysis by Steve Nison in 1991 a plethora of studies have been conducted and presented both lending support for and against the method's predictive power and value to investors.

Caginalp and Laurent (1998) were one of the first to provide strong evidence of candlestick patterns having predictive power by using statistical tests. They also quantified and standardized candlestick testing to some extent, creating a template for later studies to follow. In their study, they test eight three-day candlestick reversal patterns using z-tests on daily price data from S&P500 stocks during the period from 1992 to 1996. All eight patterns are determined to have good predictive power, and furthermore all eight patterns have statistically significant profitability in the short term.

Marshall, Young and Rose (2006) were the first to use a bootstrapping methodology to test candlestick pattern profitability. In their study, they use price data from 35 stocks in the Dow Jones Industrial Average (DJIA) over the period from 1992 to 2001. They fit the daily return data to a model, calculate the models residuals and then bootstrap them to create 500 new price series for each stock. Comparing the average returns generated using 14 candlestick patterns and 14 single line indicators on the original price data series with the average returns attained from the randomly generated price data series, they find that candlesticks patterns have no predictive power or financial value to investors.

Goo, Chen and Chang (2007) tests the profitability of 26 candlestick patterns on 25 component stocks of the Top 50 Tracker Fund and the Taiwan Mid-Cap 100 Tracker Fund during the period from 1997 to 2006. They find support for candlestick based strategies as valuable tools for investors. Furthermore they find that bearish candlestick patterns work best on 3 to 4 holding day periods while bullish patterns work best on 9 to 10 day holding periods.

Marshall, Young and Chang (2008) use the same bootstrap method as Marshall et al. (2006) to test the predictive power as well as profitability of candlestick patterns for a 10 day holding period. The tests are carried out using price data from the 100 largest stocks in the Tokyo Stock Exchange over the period from 1975 to 2002. They conclude that candlestick patterns have no predictive power nor any profitability on the Japanese stock market.

Horton (2009) studies the profitability of eight candlestick patterns on 349 stocks in the S&P500 index, comparing their returns with those of a buy and hold strategy. He concludes that the candlestick patterns Stars, Crows, and Dojis have no profitability as price predictors.

As is often the case with technical analysis, despite numerous studies and tests there is still no conclusive evidence one way or another as to the predictive power of candlestick patterns or their financial value to investors.

1.5 Limitations and Assumptions

The study limited to the period from 19 October 2007 to 31 December 2015, this is due to the fact that opening price data for OMXS30 stocks is not recorded before 19 October 2007. To use the data before 2007 the opening prices will have to be simulated, which is something that is likely to significantly decrease the reliability and validity of the study. The study is further constrained to only eight out of many candlestick patterns available, this is done to reduce data mining and as a result of limited computing power.

Candlesticks pattern analysis is often recommended to be used in consort with other indicators and tools to be most effective (Nison 1991). This paper however, only focuses on the candlestick patterns themselves, the reasoning behind this choice is that if the patterns are supposed to have any predictive power they should at least indicate so on their own. Simply adding another indicator could be construed as a sign of data mining and reduce the validity. The downside to this approach is that only focusing on one technical indicator can result in a non-statistically significant result when the addition of a complimentary indicator could make the result significant.

1.6 Research Contribution

This paper can serve as a tool for financial institutions or traders to assist in investment decisions. It also adds additional proof for the Efficient Market Hypothesis, which might dissuade some technical investors. The increased interest in investing and the increased digitalization of trading (McGowan 2011) that has occurred over the last 10 years, is likely to have drastically changed the state of market efficiency since the time earlier studies on technical analysis were performed. If this is the case, examining more recent data using methods similar to those used in earlier studies can yield different results.

Many new market participants may be overawed by the seeming endless technical indicators and strategies available, it can be an arduous task determining which ones have value and which do not. The study makes this task marginally easier by providing proof against the viability of candlesticks pattern analysis. The results show that the eight candlestick patterns cannot be used effectively as trend reversal indicators on the Swedish stock market. Moreover it shows that using the candlestick patterns as buy/short signals for short holding periods is not profitable.

1.7 Outline

Chapter 1 – Introduction

This chapter gives a short overview of what is being tested and how, while also explaining why the research is important. The results are also given but not examined in any greater detail.

Chapter 2 – Theory

The Theory chapter starts off by providing an explanation of what the efficient market hypothesis and random walk models are. Then it moves on to summarize what candlestick charting is and how it can be used to generate buy/sell/short signals for short term traders. The chapter is concluded by a basic explanation of what it means for data to be stationary and what autoregressive models are and why they are used on financial data.

Chapter 3 – Methodology

This chapter begins by providing a summary of the constraints used to define the tested candlestick patterns. After this follows a more detailed and practical explanation of the trend definition in use, the statistical tests for predictive power, profit calculation and a detailed explanation of bootstrap methodology. The chapter concludes by discussing validity and reliability.

Chapter 4 – Data

The Data chapter elaborates upon the data used as well as its collection. It details what processing software is utilized and which problems are encountered in processing the data. Furthermore it provides a detailed look into the overall trend of the price data over the period for both an index created from the 29 tested stocks and the individual stocks themselves. The last part of the data chapter briefly motivates the choices not to include courtage and taxes in the results.

Chapter 5 - Empirical Results

The Empirical Results section presents the predictive power results of all eight tested patterns as well as the average holding period return and p-values generated by buying and shorting stocks based on the appearance of the eight candlestick patterns. The section presents the results gained from both the original price data tests as well the results from the bootstrapped data.

Chapter 6 – Analysis

This chapter presents the financial and statistical implications and conclusions reached from studying the empirical results. It elaborates on what the results mean and how they relate to the efficient market hypothesis and random walk models.

Chapter 7 – Conclusion

This chapter shortly summarizes what the study set out to do and what is accomplished. It presents criticisms for the methodology and recommendations for future studies. It also explains the broader implications of the results discussed in the analysis.

2. Theory

2.1 The Efficient Market Hypothesis

The efficient market hypothesis (EMH) states that in an efficient market stock prices reflect all available current information in a rational manner. When markets are efficient, investors cannot achieve above average returns without taking on more risk. This is due to the fact that all investors have access to the same information which means that the playing field will be level and any price change is due to new information entering the market and changing expectations (Fama 1970). Therefore no single actor can consistently achieve excess returns and any such returns earned are simply temporary results of random chance. The EMH will only be completely accurate if there are no transaction costs and no cost of information acquisition. Since these assumptions are not realistic, the assumption that the market is efficient until the marginal cost attaining additional information is equal to the marginal benefit of trading with it is adopted (Elton et al. 2009).

The EMH is partly based on the logic that any historical pattern which when used yields above average returns will once it is discovered be exploited by traders until the point at which the anomaly is "farmed out" leaving the market more efficient than before. The process then continues with new patterns constantly being discovered and consequently eliminated (Elton et al. 2009).

Despite the prevalence of the EMH there are investors that have systematically beaten the market over prolonged periods of time, for example Peter Lynch (Hebner 2013) and Warren Buffett (Loomis 2012). These investors can be considered proof against the EMH, or their success could simply be the result of them being the only "survivors" out of a massive amount of investors. In theory, if a large number of investors all choose assets randomly there will always be a few who can achieve excess returns over a long period of time, appearing skilled while they are in fact only lucky (Elton et al. 2009).

The EMH as presented by Fama (1970) is segmented into three different degrees or levels of efficiency, the weakly efficient EMH, the semi-strong EMH and the strongly efficient EMH.

2.1.1 The Weak Version EMH

The weak version of the EMH states that future price movements cannot be predicted using historical price information, since all prior historical information already incorporated into the current price. Under the weak version EMH it is therefore not profitable to engage in technical analysis. Test for weakly efficient markets involve testing various indicators or regularly occurring anomalies for profitability on historical data. (Elton et al. 2009).

2.1.2 The Semi Strong Version EMH

Semi strong efficiency means that all publically available information is incorporated into the current price of any asset and since any future information is random, future prices cannot be predicted. The conclusion being that no excess returns can be achieved using publically available information or fundamental analysis. Semi strong tests usually involve testing the speed at which new information is incorporated into prices. (Elton et al. 2009).

2.1.3 The Strong Version EMH

The Strong Efficiency version of the EMH states that all information, including insider information, is reflected in the current asset prices. Thus no excess returns can be achieved regardless of what information is available to the investor. Since insider trading is outlawed this form of efficiency is not realistic. Strong efficiency tests usually examine if insiders can achieve excess returns consistently. There is little evidence supporting the strong efficiency version of the EMH (Elton et al. 2009).

2.1.4 Empirical Evidence

The empirical support for the EMH is anything but conclusive. Jegadeesh and Titman (1993) find that buying stocks that have performed well in the past and selling those that have done poorly generates significant excess returns over for three to twelve month periods. The test is carried out on stocks in New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) during the period from 1965 to 1989. Haugen (1995) also presents evidence against the EMH, by showing that strong short-term overreactions which may lead to long-term reversals exist.

Frennberg and Hansson (1993) tests the random walk hypothesis on monthly Swedish stock data for the period from 1919 to 1990 using a variance ratio and auto regression tests. They present evidence of positive autocorrelation in the returns for periods of one to twelve months and negative autocorrelation for periods of two years and longer, indicating the existence of mean reversion and therefore proof against the EMH.

Tóth and Kertész (2006) studying the 190 most frequently traded stocks on the NYSE found evidence of increasing market efficiency in the period from 1993 to 2003. Continuing a trend of increasing evidence supporting the EMH in recent years (Sewell 2011)

In conclusion, the efficient market hypothesis vs behavioral and technical analysis debate is alive and thriving with neither point of view having the final say.

2.2 The Random Walk Model

The idea that stock returns follow a random walk is based on the EMH, the theory being that if all new information is quickly incorporated into the price of an assets and the flow of information is random, then returns will move randomly. The more efficient the market, the more random the return fluctuations. Although closely related, the EMH and the random walk model are not the same thing. A random walk implies that the stock returns move independently of each other, meaning that the correlation between todays and yesterday's return should be zero or close to zero. A random walk does however, not necessarily mean that the market is efficient and populated of rational investors. In essence if the EMH is true, then the random walk theory also holds, but the reverse is not necessarily the case (Brealey et al. 2003).

If the market does in fact follow a random walk any attempt to predict future price movements on past information is doomed to failure since any future price movement is completely unpredictable (Elton et al. 2009).

2.3 Behavioral Finance

Behavioral Finance is the study of investor psychology to explain stock market pricing anomalies and inefficiencies. The theory mainly builds on the idea that investors make irrational decisions based on emotions or that investors make erroneous analysis of prices and then proceed to make incorrect investment decisions. Behavioral Finance states that these market anomalies fall into certain historical price patterns that can be identified and exploited to attain excess returns (Montier 2007).

Montier (2007) states that market actors overestimate their own ability to predict future price movements and thus over or underreact when new unanticipated information becomes available. He further stresses that price movements are largely explained by the fact that humans are short-term oriented and emotional. Furthermore investors like everyone else are prone to a herd mentality which enforces and spreads bad decisions, eventually resulting in mispricing on the stock market (Montier 2007).

As with the efficient market hypothesis there is no comprehensive behavior model or explanation for mispricing and there is evidence both supporting and discrediting behavioral theories (Brav et al. 2009). The most that can be said with certainty about the theory of behavioral finance is that the market is not efficient and excess returns can be attained by finding and exploiting inefficiencies caused by behavioral biases (Montier 2007).

2.4 Technical Analysis

Technical analysis is the collective name for a wide variety trading rules and techniques which are used to forecast future prices using only historical prices. Technical analysts base their trading decisions on the theory that future prices depend on shifts in supply and demand which can be detected in past charting patterns (Brock et al. 1992). There exists a wide assortment of methodologies and techniques for performing technical analysis, some are based on behavioral finance like candlestick charting analysis while others are based on more mathematical phenomena like Fibonacci numbers (Fisher 2003). The core assumption of technical analysis is much like the assumptions for behavioral finance that the market is not efficient and future price movements can be predicted (Elton et al. 2009).

2.5 Candlestick Charting and Pattern Analysis

Candlestick charting is in essence a more descriptive and visually easier way to grasp financial data. Its popularity no doubt results from the fact that even if an investor does not use candlesticks as a technical analysis tool, the charting method can still be used to attain a more comprehensive picture of price movements than most other charting methods can. The reason for this is that candlestick charting uses the open, high, low and close prices (OHLC) to represent a trading day instead of only using the closing price (Nison 1991).

The difference between the opening and closing price is called the candlestick body, it is black if the closing price is below the opening price and white if the reverse is true (see Figure 1). If the opening and closing price are identical a Doji is formed meaning the candlestick does not have a body. The candlesticks can also have upper and/or lower shadows (see Figure 1) which show the high and low prices achieved respectively during the trading day (Morris 2006).

An extension of candlestick charting is as a technical analysis tool, wherein formations of certain candlesticks are used to predict future price movement. There are many different distinctive candlesticks or combination of candlesticks that offer various levels of predictive power. All the patterns are based on the psychology of the market and a pattern usually consist of one to three candlesticks but seldom more than five. Some patterns stand on their own, while others need confirmation to be reliable. Confirmation is often given in the form of a higher opening- or closing price compared to the previous day in which the candlestick pattern was identified (Morris 2006).

The candlestick patterns can be sorted into two categories, continuation or reversal patterns. Continuation patterns indicate that the current trend will continue, while reversal patterns indicate that the current trend will reverse. Reversal patterns are either bullish or bearish, with the bearish patterns typically being inverses of the bullish patterns or vice versa (Morris 2006).

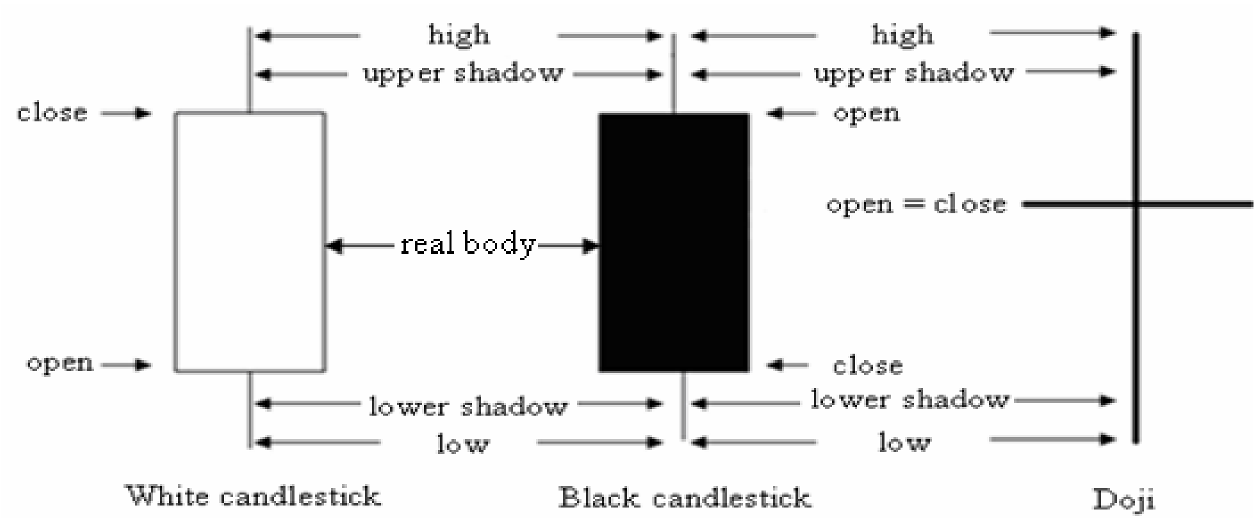


Figure 1: Candlestick Construction: Depicts the different parts that make up a candlestick on any given trading day. **Source:** Goo, Chen and Chang (2007)

2.6 Candlestick Patterns

The Hammer and the Hanging Man: Both are single candlestick trend reversals patterns which occur in a downwards- and upwards trend respectively. According to Nison (1991) the patterns have small real bodies with long lower shadows at least 2 times the body's size and a non-existent or very small upper shadow (see Figure 2). Morris (2006) explains that the color of the candlestick becomes more bullish if it is white in a downwards trend and more bearish if it is black in an upwards trend, but both colors are considered valid, he goes on to say that the upper shadow should be no more than 10 percent of the high-low range. Nison (1991) recommends waiting for confirmation of the pattern before committing to any action.

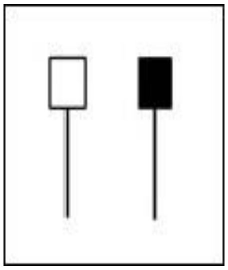
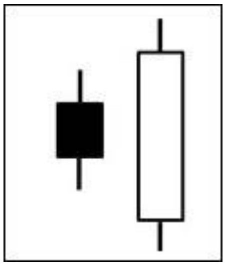


Figure 2: The Hammer or Hanging Man, depending on trend, both black and white bodies are valid for each pattern.

The psychology of the Hammer: The market opens in a bearish trend and actors start selling, however the momentum shifts, the bears begin to lose control resulting in a rally with the price closing around the opening price. Market participants will observe that the bearish trend has abated and will therefore be hesitant to enter into a bearish position, bullish actors will be encouraged to enter long positions, thus prompting a future trend reversal (Morris 2006).

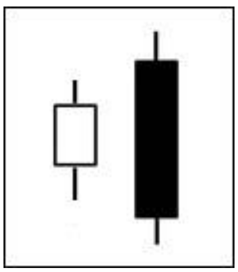
The psychology of the Hanging Man: The market opens in an upwards trend and the price falls dramatically during the day, the price then rallies to close around the opening price. Market participants observe that the bullish trend may have begun to slacken off and are therefore hesitant to maintain their long position the next day, prompting a future trend reversal (Morris 2006).

The Engulfing pattern: Is a major two-day reversal pattern comprised of two real bodies of opposite color. The second candle's body completely engulfs the previous day's candle's body (see Figure 3 and 4). The shadows are not part of the pattern. For the pattern to be a viable indicator the market needs to be in a clear upwards or downwards trend depending on if it is a bullish or bearish pattern (Nison 1991).



The psychology of the Bullish Engulfing pattern: The Market is in a downwards trend when a white body open below the previous day's closing price and rallies to completely engulf the preceding days black body (see Figure 3), the change is drastic and the downtrend appears to have stopped with the bulls gaining control of the market (Nison 1991).

Figure 3: The Bullish Engulfing Pattern.



The psychology of the Bearish Engulfing pattern: In an upward trend a small white body is followed by an open at a new high on the second day, the new high cannot be maintained and a sell-off calumniates in a close lower than the previous day's body (see Figure 4). The momentum of the upward trend has abated, the bulls are discouraged from staying long and a major trend reversal towards a downtrend is possible (Nison 1991).

Figure 4: The Bearish Engulfing Pattern.

The Piercing Lines: Is a bullish bottom reversal indicator comprised of two candlesticks, the first candlestick has a black body and the second a white body. The white body opens well below the previous day's low then rallies "piercing" the black body until it closes above the middle of the black body (see Figure 5). The greater the degree or piercing the stronger the reversal pattern (Morris 2006).

The psychology of the Piercing Lines: On the first day, the black body continues the bearish trend. On the second day, the market opens below the low of the first day, thus continuing the bearish trend. When the market rallies to close above the midpoint of the first day's body the bears begin to question their position. The bulls are also encouraged by the fact that a new low was unable to be maintained, the shifts in mood opens a window for a trend reversal to begin (Nison 1991).

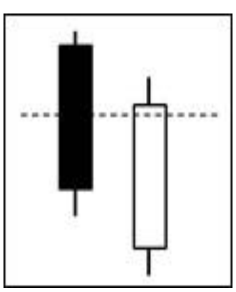


Figure 5: The Piercing Lines Pattern.

The Dark-Cloud Cover pattern: Is a bearish top reversal pattern and the inverse of the Piercing Lines pattern, the first candlestick has a white body and the second a black body. The black body opens above the previous day's high then declines sharply "piercing" the white body until it closes below the middle of the white body (see Figure 6). The greater the degree or piercing the stronger the reversal pattern (Nison 1991).

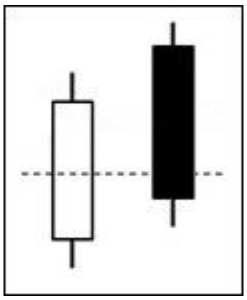


Figure 6: The Dark Cloud Cover Pattern.

The psychology of the Dark-Cloud Cover pattern: The white body continues the uptrend, the next day the market opens above the high of the previous day, a clear bullish sign. The new top is however unable to be maintained and when the price closes below the midpoint of the previous day's body the bulls fear a top has been reached and begin to question their position which opens a gate for a trend reversal. (Nison 1991).

The Harami pattern: Is the reverse of the Engulfing pattern meaning it is a two-day pattern consisting of two candles of opposite color wherein the second days candle is engulfed by the first (see Figure 7 and 8). The candles color is not as important as it is for the Engulfing pattern as long as the two days are of opposite color. Although not considered vital, it is still best if the first candle's color reflects the trend of the market. Like the Engulfing pattern the shadows are not considered, only the real bodies are of importance. Unlike the Hammer/Hanging Man or Engulfing patterns the Harami is not considered a major reversal pattern (Nison 1991).

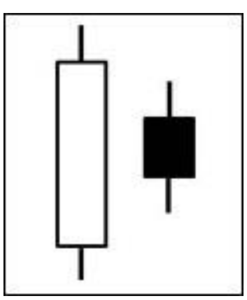


Figure 7: The Bearish Harami Pattern.

The psychology of the Bearish Harami pattern: The market is in an uptrend which is continued by the white candlestick on day one, the next day the price opens lower but stays within the range of the previous day's real body (see Figure 7). The pattern signals a potential top and at the very a least a lowering of momentum, the bulls begin to question the strength of the uptrend and start considering closing out their positions (Nison 1991)

The psychology of the Bullish Harami pattern: In a downtrend a long black day occurs confirming the trend, on the following day the price opens higher than the close of the previous day (see figure 8). The higher open creates doubt among the investors who are short, they cover their positions resulting in a price rally. The rally is however stifled by speculative short position traders who have yet to enter the market, they see the increase in price as an opportunity to cash in on the inevitable continuation of the downtrend. Confirmation on the third day results in the short positions quickly being covered leading to a further rally, a trend reversal has begun (Nison 1991).

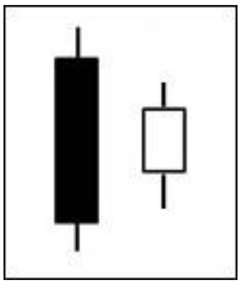


Figure 8: The Bullish Harami Pattern.

2.7 The Simple Moving Average

The Simple moving average (MA) is a trend smoothing tool which calculates the mean of the prices for an asset over a set period of days. The MA eliminates temporary and extreme fluctuations in price and simplifies the identification of a trend. The more days and therefore prices that are included in the MA the less emphasis is placed on each individual price. Hence, more days results in a smoother trend and less risk for single extreme price shifts to influence the trend. Including more days in the MA results in fewer incorrect trend reversal signals, the cost however, is a slower recognition of actual trend reversals (Investopedia 2016).

2.8 Stationarity[1]

A stationary data series is defined as having a constant mean, variance and autocorrelation for any given lag. In a stationary process a shock dies out over time, diminishing with every observation from its occurrence, in essence, a shock at time t will have a smaller effect on (t+1) and even smaller (t+2) etc. For non-stationary data this is not the case, rather than dying out, the effect of a shock can continue forever. There are two types of non-stationary models, the trend-

[1] Note that the entire text involving stationarity and non-linear model uses Chris Brooks, Introductory Econometrics for Finance 2014 as a source unless otherwise stated – This notation is meant to avoid excessive referencing to the same source throughout this section of the paper.

stationary process model, which is stationary around a linear trend and the random walk model, of which we are only interested in the latter.

The efficient market hypothesis and the rational expectation hypothesis states that asset prices should follow a random walk with drift, such a model is given by the equation:

$$y_t = \mu + y_{t-1} + u_t$$

Where y_t denotes the dependent variable, μ denotes the mean, y_{t-1} is the dependent variable lagged once, and u_t is the error term.

The random walk model can in turn be modified by adding the θ term:

$$y_t = \mu + \theta y_{t-1} + u_t$$

In which case the model falls into three categories depending on the value the θ term.

The first category is given by:

$$|\theta| < 1 \Rightarrow \theta^t \rightarrow 0 \; as \; t \rightarrow \; \infty$$

In which case the model is stationary since the shocks will gradually dissipate over time.

The second category is given by:

$$\theta = 1 \Rightarrow \theta^t = 1 \; \forall \; t$$

In which case:

$$y_t = y_0 + \sum_{t=0}^{\infty} u_t \; \; as \; t \rightarrow \; \infty$$

Where the current value of the dependent variable y_t is simply an infinite sum of the past shocks and whatever starting point y_0 exists. When $\theta = 1$ a process is said to have a unit root, and is non-stationary since the shocks never die out.

The third category in which $\theta > 1$ describes a process in which any shocks builds upon another and neither will ever die out. This category will not be considered further since it has few real world applications.

2.8.1 The Unit Root Test

The purpose of the unit root test, developed by (Dickey and Fuller 1979) is to ascertain if time-series data is stationary. It tests the null hypothesis $H_0: \theta = 1$ against the one-sided alternative hypothesis $H_A: \theta < 1$ for an autoregressive model AR (t):

$$y_t = \theta y_{t-1} + u_t$$

If a unit root exists, shocks will not dissipate over time and the data-series will not be stationary. The equation for the dependent variable can be transformed into the equation:

$$\Delta y_t = \psi y_{t-1} + u_t$$

By subtracting y_{t-1} on both sides, where $\psi = \theta - 1$ in which case $H_A: \psi = 0$ and $H_A: \psi < 0$. The unit root test is unchanged, but the test is easier to perform and the results easier to interpret.

2.9 Non-Linear Models

Financial return data often does not follow a completely normal distribution, it is often plagued by issues like leptokurtosis, volatility clustering and leverage effects. Leptokurtosis means that the distribution has fat tails and a distinct peakedness at the mean resulting from, large but infrequent deviations from the mean. Volatility clustering means that once a shock to the market characterized by high fluctuations in returns occurs, it is likely to persist over time dying out only gradually. The predominant theory for why volatility clustering exists in financial data is that information tends to be published in chunks rather than being a constant flow over time. Leverage effects means that volatility rises more in the wake of large prices falls than in large price rallies.

In order to fit time-series data which suffers from these effects to a model, a non-linear model is needed. There are many non-linear models but only a few are considered effective for modeling financial data, Campbell et al. (1997) defines non-linear models as:

$$y_t = g(u_{t-1}, u_{t-2}, \dots) + u_t \sigma^2 (u_{t-1}, u_{t-2}, \dots)$$

In which the function g is dependent on past error terms and the variance σ^2 is dependent on all error terms past and present. Models can thus be linear in mean and variance in which case

ARIMA models are appropriate or linear in mean and non-linear in variance in which case GARCH models are needed.

2.9.1 Autoregressive Volatility Models

Auto regressive (AR) volatility models are a simple means of estimating the non-constant volatility of time series data, it uses proxies to obtain the daily volatility. One of the standard proxies used is the squared daily returns, in which case the squared return of day t becomes the volatility estimate for day t.

2.9.2 Autoregressive Conditionally Heteroscedastic (ARCH) Models

The ARCH model is a non-linear model, it is useful due to the fact that it accounts for financial data often producing errors that are heteroscedastic and a variance that clusters. In order to model data with these issues the ARCH model uses a conditional variance denoted σ_t^2, which depends on the previous value of the error term squared u_{t-1}^2:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$$

The model is an ARCH (1) model due the fact that the conditional variance only depends on one lagged squared error. The conditional mean which describes how the dependent variable y_t varies over time and u_t which is a normally distributed error term is modeled with a simple regression equation:

$$y_t = \beta_0 + \sum_{i=1}^{i} \beta_i x_i + u_t$$

$$u_t \sim N(0, \sigma^2)$$

2.9.3 Generalized ARCH (GARCH) Models

The GARCH model is an extension of the ARCH model, it has the same possible equations for the conditional mean as the ARCH. The models differs in that the GARCH allows the conditional variance to be dependent not only upon past squared errors but also on its own previous lags, which means that its conditional variance is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2$$

$\sigma_t^2 = The\ Conditional\ Variance$

$u_{t-1}^2 = The\ squared\ Error\ Term\ lagged\ once$

$\sigma_{t-1}^2 = \ The\ Condtinal\ Variance\ lagged\ once$

The model is known as the GARCH (1.1) model, so called, since it has one lag of squared errors terms and one lag of conditional variance. The reason the GARCH is used instead of the ARCH model is that it is more efficient and avoids overfitting. This is due to it using only three parameters to account for an infinite number of squared errors to influence the current conditional variance, while the ARCH model would have to include every past squared error term in the equation.

2.9.4 The GARCH-In-Mean Model

Investors are generally assumed to demand higher returns when faced with greater risk, one problem with the GARCH (1.1) model in this respect is that it does not allow for any interaction between the conditional mean and the conditional variance. To remedy this issue, Engle, Lilien and Robins (1987) developed the GARCH-In-Mean model, in which the conditional variance directly affects the conditional mean. The model allows the conditional mean to vary over time as the degree of risk varies. The model is given by:

$$y_t = \alpha + \gamma\sigma_t^2 + \beta_1 u_{t-1} + u_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_2\sigma_{t-1}^2$$

$$u_t \sim N(0, \sigma^2)$$

$y_t = The\ Conditional\ Mean$

$\sigma_t^2 = The\ Conditional\ Variance$

$\sigma_{t-1}^2 = The\ Condintional\ Variance\ lagged\ once$

$u_{t-1} = The\ error\ term\ lagged\ once$

$u_t = The\ Error\ term$

The γ term can be interpreted as a risk premium, if it is positive and statistically significant, then the returns are dependent on the conditional variance (risk). The error term u_t is conditionally normally distributed and serially uncorrelated. And the conditional variance is a linear function of the square of the last period's error term and the last period's variance. The model can therefore properly account for volatility clustering (Brock et al. 1992).

2.10 Bootstrapping

Bootstrapping is a process of creating new random data based on existing data, while keeping the properties of the original data. Suppose a sample of data exists for which $y_t = y_1, y_2, \dots, y_t$ and the goal is to estimate a parameter δ, an estimate can be obtained by studying a series of bootstrapped data. This is done by taking n samples of size T with replacement from the original y_t-series to create new data and then estimating the parameter δ for each new series of bootstrapped data. A series of estimated δ values are thus obtained and they can be used to estimate the true value of δ. This procedure in essence involves sampling from the sample, treating the sample as the population from which it is originally drawn.

Bootstrapping in finance is often applied to detect if data-snooping is present in tests for technical trading rules. Data mining denotes the process of either creating new trading rules based on existing data and then testing those same rules for significance on a certain data or applying a multitude of technical rules on price data and choosing any trading rules that by chance work on the particular set of data.

The bootstrapping methodology when applied to finance can involves bootstrapping the returns from time-series price-data, this creates data with on average the same distributional properties as the original, but eliminates any linear or non-linear autocorrelation.

In order to emulate the same price drift, variance and autocorrelation characteristics in the bootstrapped data that the original possess a different method than the one given above is called for. This method is in essence comprised of bootstrapping the residuals rather than the returns.

The procedure involves first modeling the returns using an autoregressive model such as an AR (p), ARCH or GARCH model, whichever fits the data best. Then obtaining its residuals and bootstrapping them with replacement onto the models equation of estimated parameters obtained by the autoregressive model. On average this procedure produces a return series that has the same autoregressive properties as the original series, meaning it can contain auto regression in the residuals and variance.

3. Methodology

3.1 Candlestick Patterns and their Definitions

Candlestick pattern analysis is not an established theory nor one that is rigorously defined. There are guidelines and recommendations for each pattern in prominent literature by authors like Nison (1991) and Morris (2006), it is however largely up to each analyst to decide which constraints to apply to the definitions of each pattern. There are many options, one is to wait for confirmation of a candlestick pattern before it's deemed a real pattern. Confirmation for the study is defined as the closing price being higher on the day following the candlestick being identified, than the closing price of the last day of the candlestick pattern. Other options include only recognizing pattern as real when the volume is sufficiently high or when the price movement during the day is sufficiently large (Nison 1991). Since there exists such an ambiguity in regards to what a candlestick pattern is supposed to look like, a full outline of the study's constraints for all candlestick patterns tested are provided in Appendix 8.2. Furthermore their excel formulae are presented in Appendix 8.3. The eight candlesticks patterns tested are listed in Table 1.

Table 1: Candlestick Pattern

Displays the names of the eight candlestick patterns tested in the study

Bullish Patterns	**Bullish Patterns**
The Hammer	The Hanging Man
The Bullish Engulfing	The Bearish Engulfing
The Piercing Lines	Dark Cloud Cover
The Bullish Harami	The Bearish Harami

3.2 Definition of Trend with Moving Averages

All eight candlestick patterns are trend reversal patterns and as such they will only be valid if they occur in an actual upwards or downwards trend depending on if they are top (bearish) or bottom (bullish) reversal patterns (Nison 1991). This essentially means that a top reversal pattern in a downward trend is an irrelevant indicator and will be ignored. The reliance of a previous trend prompts the need for a rigorous definition of trend, this is done by applying a moving average methodology.

Lu et al. (2011) use a five-day moving average and find that significant returns can be attained using candlesticks. Marshall et al. (2006) and Marshall et al. (2008) both use a ten-day exponential moving average and find no significant returns. Caginalp and Laurent (1998) and Lu (2012) utilize a three-day moving average, and both find significant returns. In order to define trend for this study, we use a five-day moving average in line with the methodology employed by Lu and Shiu (2009) as well as Lu et al. (2011). The choice is motivated by it the middle ground between the ten-day moving average that Marshall et al. (2006) employs and the three-day moving average employed by Caginalp and Laurent (1998).

The five-day moving average MA_t^5 on any given day $t = 1,2,3 \dots n$ is given by:

$$MA_t^5 = \frac{1}{5}[p_{t-4}^c + p_{t-3}^c + p_{t-2}^c + p_{t-1}^c + p_t^c] \tag{1}$$

Where p_t^c denotes the closing price on day $t = 1,2,3 \dots n$

To identify upward and downward trends the methodology developed by Caginalp and Laurent (1998) is employed with the slight variation of a five-day MA instead of three-day MA.

An upward trend is identified when the five-day MA is strictly increasing consecutively for at least five of the past six days. More rigorously stated: At least four of the following five inequalities have to hold for an upwards trend to be identified:

$$MA_{t-5}^5 < MA_{t-4}^5 \dots < MA_{t-1}^5 < MA_t^5 \tag{2}$$

And a downwards trend is similarly defined, the difference being that the MA has to be strictly decreasing instead rather than increasing. Thus, at least four of the following five inequalities have to hold for a downwards trend to be identified:

$$MA_{t-5}^5 > MA_{t-4}^5 \dots > MA_{t-1}^5 > MA_t^5 \tag{3}$$

The definition of trend encompassing 6 days is motivated by the focus of the study being on short term. The allowance for one inequality deviation is motivated by it resulting in a more flexible definition of trend.

3.2.1 A Break in the Trend

In order to define a trend reversal, the methodology outlined by Caginalp and Laurent (1998) is adopted. The definition of a successful trend reversal according to their methodology is illustrated by the following scenario which depicts the process of a successful reversal following a Hammer pattern:

On day (t) a stock is in a downwards trend as defined by Equation (3) and the next day $(t+1)$ a Hammer pattern is identified, the pattern is confirmed the next day $(t+2)$ by the closing price p_{t+2}^{c} being higher than on the previous day p_{t+1}^{c}. The trend is successfully reversed when the following day's closing price p_{t+3}^{c} is lower than the three-day average of the next 3 consecutive days closing prices according to equation 4:

$$p_{t+3}^{c} < \frac{1}{3}[p_{t+4}^{c} + p_{t+5}^{c} + p_{t+6}^{c}] \quad (4)$$

For a bearish pattern, a successful trend reversal is defined by the closing price on day $(t+3)$ being higher than the average of the 3 following days:

$$p_{t+3}^{c} > \frac{1}{3}[p_{t+4}^{c} + p_{t+5}^{c} + p_{t+6}^{c}] \quad (5)$$

A failure of a bullish pattern is confirmed by the closing price p_{t+3}^{c} being higher than the average of the following three days (see Equation 5).
A failure of a bearish pattern is given by the closing price p_{t+3}^{c} being lower than the average of the following three days (see Equation 4).

Although rare, it is also possible for a pattern to result in continuation, which means that the trend is simply stalled following the identification of a candlestick pattern. The trend being stalled is not counted as a failure nor as a success. A continuation is defined as:

$$p_{t+3}^{c} = \frac{1}{3}[p_{t+4}^{c} + p_{t+5}^{c} + p_{t+6}^{c}] \quad (6)$$

3.2.2 A Statistical Test for Predictive Power

In order to test if a candlestick is a statistically significant trend reverser we need to examine if the occurrence of a candlestick pattern in a downtrend (uptrend) increases the probability of prices moving higher (lower). This is done using the Caginalp and Laurent (1998) methodology, assuming a binominal distribution approximated to the normal distribution. The statistical tests are performed using a 5% alpha level for significance, applied to a one-sided t-test.

The first step is to ascertain the overall probability of a trend reversal occurring, here denoted p_0. This is done by first counting the number of times a downward trend reversal occurs regardless if a candlestick is present or not, this count is denoted n_D. More specifically n_D is given by the number of times a downtrend on any given day (t) is followed on day $(t + 3)$ by a successful upward signal as defined by equation 4.

The next step is to calculate the total number of days that are in a downtrend as defined Equation 3, denoted(n_A). The overall probability of a downwards trend being reversed p_0, is then given by the equation:

$$p_0 = n_D/n_A$$

The probability p_0, can according to the central limit theorem be assumed to be the population mean if the sample satisfies the constraint $n_A p_0(1 - p_0) > 5$ (Körner and Walgren 2006).

The next step is to repeat the process used to count (n_D), but in this case only count the number of times a candlestick reversal pattern is present prior to the trend reversal, this number is denoted (n_C). Next, the number of times the pattern occurs in a downwards trend is counted, regardless if it is followed by a successful reversal signal as defined by equation 4 or not, the number is denoted (n_E).

It is now possible to calculate the probability of trend reversal success p_C for the candlestick pattern:

$$p_C = n_C/n_E$$

Körner and Walgren (2006) state that the standard deviation of the mean is then given by the square root of the variance for a binomially distributed variable according to the equation:

$$\sigma = \sqrt{n_C p_0(1 - p_0)}$$

Once the probabilities and standard deviations are calculated, the next step is to set up the null and alternate hypothesis:

$$H_0: p_1 - p_0 = 0$$

$$H_1: p_1 - p_0 \neq 0$$

The t-statistic is calculated by comparing the difference between the expected value $n_C p_0$ (the expected number of times a candlestick would be followed by a successful reversal signal) and sample value $n_C p_1$ (the actual number of times the candlestick is followed by a successful signal), measured in the number of standard deviations from the null hypothesis by:

$$t = \frac{n(p - p_0)}{\sigma}$$

To calculate the t-statistic for the bearish patterns, the process is adapted by changing the downtrends to uptrends and reversals up to reversals down.

3.3 Profit Calculation and its Statistical Test

The study is concerned with fixed holding periods from one to ten days, profits are calculated with the following assumptions: Positions are entered into the opening price of the day following the candlestick patterns appearance or following the confirmation of a candlestick pattern and the positions are exited at the closing price of the last day of the holding period. The profits or holding period returns for long and short positions are calculated with the following equations:

$$R_{long} = \frac{p_{t+n}^{c} - p_{t+4}^{o}}{p_{t+4}^{o}}$$

$$R_{short} = -\frac{p_{t+n}^{c} - p_{t+4}^{o}}{p_{t+4}^{o}}$$

Where p_{t+4}^{o} is the opening price of the day following the appearance candlestick pattern and p_{t+n}^{c} is the closing price n day later. As an example of a four day holding period: If at the end of day (t) the five-day moving average closing price has been increasing consecutively over the past five days, then an uptrend is in effect. The following day (t+1), a Hanging Man pattern is observed and confirmed on day two (t+2), a short position is then entered into at the opening price on day (t+3) and closed out at the closing price three days later day (t+6).

Following the calculation of the mean rate of return of each candlestick during each of the holding periods, the average rates of return are t-tested for significance, with the null and alternate hypothesis:

$$H_0: \mu_{ij} = 0$$
$$H_1: \mu_{ij} > 0$$

Where μ_{ij} represents the mean rate of return for each holding period $i = 1,2,3 \dots 10$ and candlestick pattern $j = 1,2,3 \dots 8$. To test the null hypothesis a simple one sided t-test is used which is defined by:

$$t = \frac{\bar{X}_{ij} - \bar{X}_0}{\sqrt{S_{ij}/n_j}}$$

Where $\bar{X}_{ij}$ is the sample average holding period return for each holding period $j = 1,2,3 \dots 10$ and candlestick pattern $i = 1,2,3 \dots 8$, n_j corresponds to the number of trades, S_{ij} is variance of the sample, $\bar{X}_0$ denotes the tested hypothetical mean, and (S_{ij}/n_j) is the standard error of the mean.

3.4 Bootstrapping

Due to financial data often having fatter tails (leptokurtosis) than a normal distribution, autocorrelation, and conditional heteroscedasticity, a simple t-test is not always applicable (Brooks 2014). To account for this, a bootstrapping approach which accounts for these problems is used to generate data by drawing from a sample with replacement.

The first step involves creating daily returns from the individual stock's closing prices in order to make the data stationary. Once the returns are obtained a unit root test is applied to make sure the data is stationary. The unit root null and alternative hypothesis are:

$$H_0: r\ has\ a\ unit\ root$$
$$H_1: r\ has\ a\ does\ not\ have\ a\ unit\ root$$

Once the null hypothesis is rejected and the data is considered stationary the next step is to choose which null-model to fit the data to. Based on the precedence set by Marshall et al. (2006) and (2008), the closing price data is fitted using the GARCH (1.1), Exponential GARCH

(EGARCH), GARCH In-Mean (GARCH-M), and the AR (1) models. The results are very similar for all models and therefore a single model is chosen. The GARCH-M model is chosen, this is motivated by it being the most realistic model for financial data, since it allows for the conditional mean to be influenced by the conditional variance. Another reason for using the GARCH-M is the fact that it is the model Marshall et al. (2006) and (2008) uses. The GARCH-M is given by equations 7 through 9, for a more detailed explanation of the model see 2.7.6.

$$y_t = \alpha + \gamma\sigma_t^2 + \beta_1 u_{t-1} + u_t \tag{7}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2 \tag{8}$$

$$u_t \sim N(0, \sigma^2) \tag{9}$$

Once the parameters for equations 7 and 8 are estimated, the residuals are generated and then redrawn with replacement to form a new residual series. New variance and return series are then generated using the estimated parameters for equations 7 and 8 by drawing on the randomly generated residual series. This procedure creates a return series with the same volatility, drift and unconditional distribution as the original stock. The constructed returns will however, be independently and identically distributed (Brock et.al 1992). After constructing the new return series, the new closing prices need to be calculated:

The closing price for the constructed data series on day 1, denoted P_{1B}^c, is attained from the equation:

$$P_{1B}^c = (1 + r_1) * P_0^c$$

Where r_1 denotes the constructed return for day 1, and P_0^c is the original closing price for day 0.

The closing price on day 2 for the constructed price series P_{2B}^c is attained from the equation:

$$P_{2B}^c = (1 + r_2) * P_{1B}^c$$

Where r_2 is the constructed return for day 2, the process is then repeated to attain each closing price on day $t = 3,4,5 \ldots n$ for the entire test period. The entire procedure is repeated 500 times, each time with a new bootstrapped residual series, resulting in new closing price series, all of which have the same closing price as the original stock on day 0 and then diverge. The randomly generated closing price-series have on average, the same price drift and conditional variance as the original stock.

The next step is to attain the opening prices for the new bootstrapped data series. These are generated, by first calculating the percentage differences between the open and closing prices for all trading days on the original stock with the equation:

$$D_t = \ln\left[\frac{P_t^o}{P_t^c}\right]$$

Where D_t denotes the percentage difference, P_t^o the opening price of the original data, and P_t^c the closing price of the original data for day $t = 1,2,..n$.

The differences are then bootstrapped to attain a new random open price percentage difference series. These are used to construct the new opening prices series with the following equation:

$$P_{tB}^O = e^{D_t} * P_{tB}^c$$

Where e^{D_t} is the exponiated difference D_t, P_{tB}^C is the constructed closing price and P_{tB}^O is the constructed opening price, all for any day $t = 0,1,2 \ldots n$. The method is repeated with slight variations for the high and low percentage differences to attain the new random high and low price series.

Once the new OHLC time-series data is constructed, the same candlestick trading and trend rules which are applied on the original data are applied to the new price series. The average returns for each candlestick pattern and holding period are then compared to that of the original stock to see which is larger. This process is repeated for each of the 500 randomly generated OHLC price-data series. If the random price-series generates lower holding period returns than the original less than five percent of the time, a candlestick pattern's average holding return is determined to be statistically significant. The test is therefore a one sided test with a 5% alpha level (Marshall et al. 2006)

The choice to bootstrap each stock's data-series 500 times is motivated by it being enough to give a good approximation of the return distribution of the original data (Brock et.al 1992).

3.5 Reliability and Validity

Reliability is a measure of the trustworthiness and objectivity in the research, it measures to which degree the same study can be performed with the same method to attain the same results. Validity states to which degree the study measures that which is it meant to examine, factors which affect validity include the instruments quality and the research design (Körner & Wahlgren 2012).

Despite including only stocks that are currently in the OMXS30 index which suffers from survivor bias, the study is not considered to suffer from the same. This is due to the fact that only the very short term is examined which places very little reliance on long term trends. Furthermore the returns from the technical trading strategy are not compared to buy and hold returns but rather to returns generated from bootstrapped price-series-data which do not suffer from any bias since they are randomly generated. Therefore survivor bias is not considered to have any effect on the reliability of validity of the study.

The only factor negatively affecting the reliability is the human error factor, which is considered to be small but present. The human error factor arises from the fact that mistakes can occur during the process of manually entering data into Excel and Eviews.

In conclusion, since most research methodology is based on previous peer reviewed research papers and the results answer the main questions asked, the reliability and validity are considered to be very high.

4. Data

4.1 Data Overview and Collection

The study uses secondary data exclusively, focusing on 29 of the 30 individual stocks comprising the OMXS30 index. The only stocks included in the index are the 30 most traded stocks on the Swedish stock market. The tests are performed on the time-series price data of the 29 stocks, which is recorded during the approximate 8 year period from 19 October 2007 to 31 December 2015. The data is attained through NASDAQ OMX Nordic database in the OHLC format. Since the data is collected from NASDAQ's official website it is considered of high quality. Furthermore, the data is already adjusted for dividends, splits and emissions.

4.2 Data Selection

The stocks comprising the OMXS30 are thought to be a good approximation of the Swedish stock market since they are the most traded stocks and thus not subject to isolated inefficiencies that might occur in low traded stocks. Furthermore, according to Morris (1995) technical analysis is more applicable to frequently traded stocks, making the index stocks a good choice. Although the OMXS30 is adjusted every six months in order to properly reflect the changes in the Swedish stock market, only the stocks included in the index 20 April 2016 are used. The Alfa Laval AB stock is excluded from the study due to the fact that open and high price data is not recorded for the entire eight year period. Consequently only 29 of the most traded stocks in the Swedish stock market are included in the study.

The time period is chosen for several reasons, the main one being that opening price data is not recorded for any stock prior to 19 October 2007. The period examined encompasses a crash, from 2007 to 2009, and a recession, from 2008 to 2015 (see figure 9). Since the period encompasses an entire bust-recession cycle it is considered to give a good overall picture of the Swedish economy and therefore the stock market. The picture is however not complete, given that no "boom" is contained within the data period.

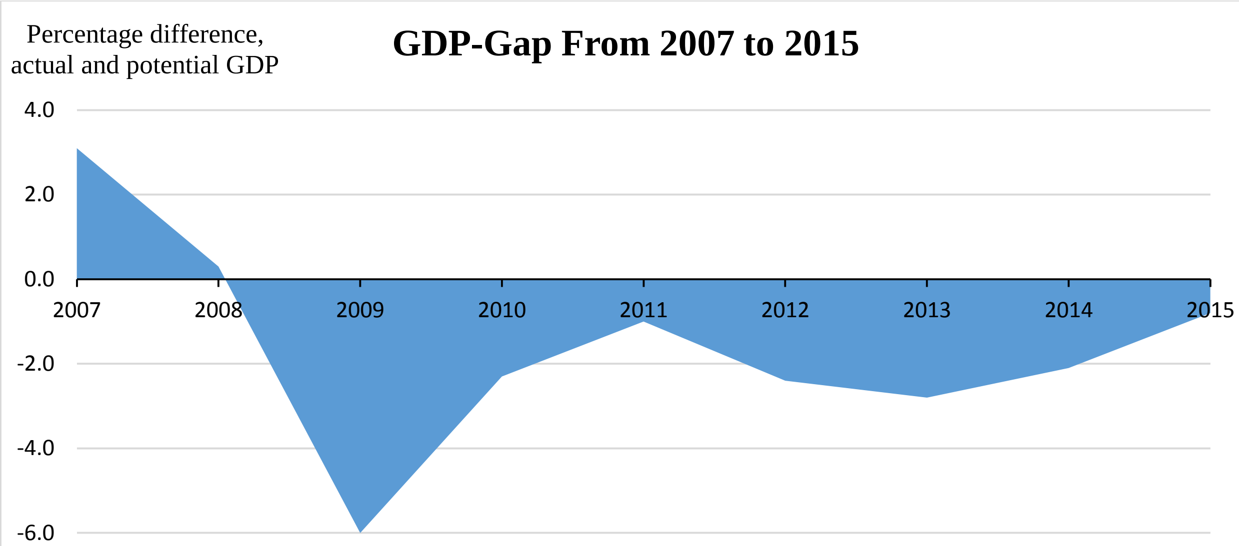


Figure 9: The GDP-Gap for Sweden, calculated as the percentage difference between actual and potential GDP, from 19 October 2007 to 31 December 2015. (Source: Carlgren, Ekonomifakta 2016-05-11)

4.3 Price Trends

Despite the economy being mostly in recession during the examined period, the value of all the 29 stocks combined into an equally weighted index which is adjusted for dividends has increased in price from around 129 to 185 SEK or by 43,4% (see Figure 10).

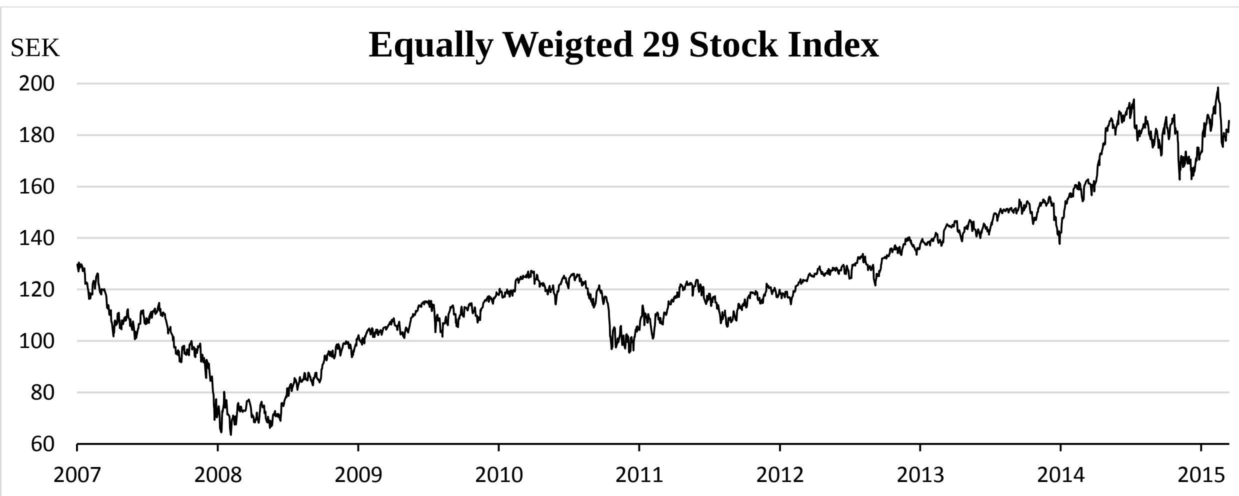


Figure 10: Depicts the daily closing price of an equally weighted index for the 29 examined stocks for the period from 19 October 2007 to 31 December 2015.

The overall price trend presented in Figure 10 is positive but the stock trading is not carried out on an index of stocks but rather separately for each stock. Therefore, the focus lies on the price movement for each of the 29 stocks. The percentage price increase of each stock for the entire period (see Figure 11) clearly shows why the index in Figure 10 has increased. The overarching percentage price change trend of the 29 stocks is positive, with 19 stocks increasing in price and 10 decreasing (see Figure 11).

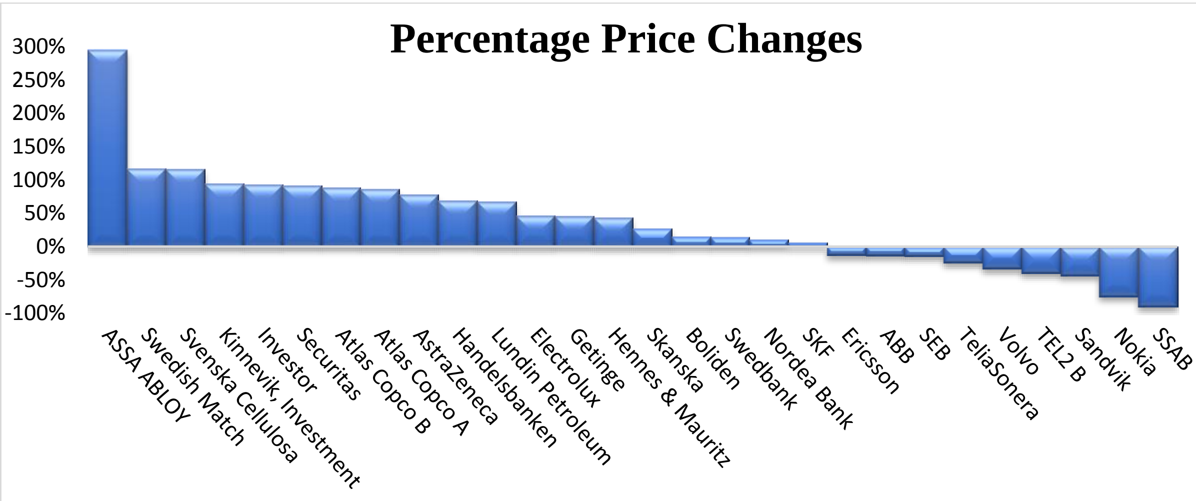


Figure 11: Depicts the individual percentage price changes for each stock of the 29 tested stocks for the period starting 19 October 2007 and ending 31 December 2015. Fingerprint Cards price percentage change over the period (5882%) is excluded due to its extreme outlier value which, if included will distort the graph.

The largest price percentage increase across all stocks during the period is achieved by the Fingerprint Cards Holding stock which increased by 5882%. The stock is excluded from the graph in Figure 11 due to its extreme value otherwise distorting the graph. Fingerprint Cards Holding's closing price increased from 9.58 SEK to 526 SEK over the period. (For a full and more exact accounting of the percentage price changes, see Appendix Table 3).

4.4 Data Processing

The data is studied using Eviews and Microsoft Excel. The trading days for which there is no OHLC data recorded are excluded from the study. There are three such days, these occur on 24 July 2011, 1 July 2012 and 6 July 2011. Although the price data is missing across all stocks for these three days, no explanation as to why this is the case is found. Since the data recording stop occurred on the same day for all 29 stocks their elimination from the time-series data is not considered to affect the reliability or validity of the study.

4.5 Taxes

Taxes are not be considered in this study, this is motivated by that including taxes distracts from the main focus which is to test if a trading strategy is profitable. Furthermore taxes are not the same across the world and therefore additional assumptions will have to be made to properly account for them.

4.6 Courtage

The only relevant transaction costs when trading with stocks is the courtage costs. The current courtage cost is very low corresponding to 0,085% of the transaction value, which is the "medium" courtage class cost on the internet based trading hub Avanza (Avanza 2016). Bigger customers such as firms or banks are however likely to have access to even lower courtage costs. If courtage is assumed to be 0,085% while another market actor is in fact faced with a lower courtage, then this incorrect assumption could result in a false negative or type II error. This, of course, means that the hypothesis of the trading strategy being unprofitable is not rejected although it should be. With this in mind, courtage costs are not applied to the empirical result.

5. Empirical Results

5.1 Reversal Results

Out of the total 59 653 trading days only 4127 buy/short signals in the form of candlestick patterns are identified, which corresponds to roughly one signal for every 15 trading days (Appendix Table 1). Put in another way, buy or short signals are identified for 7% of the trading days (see Figure 12).

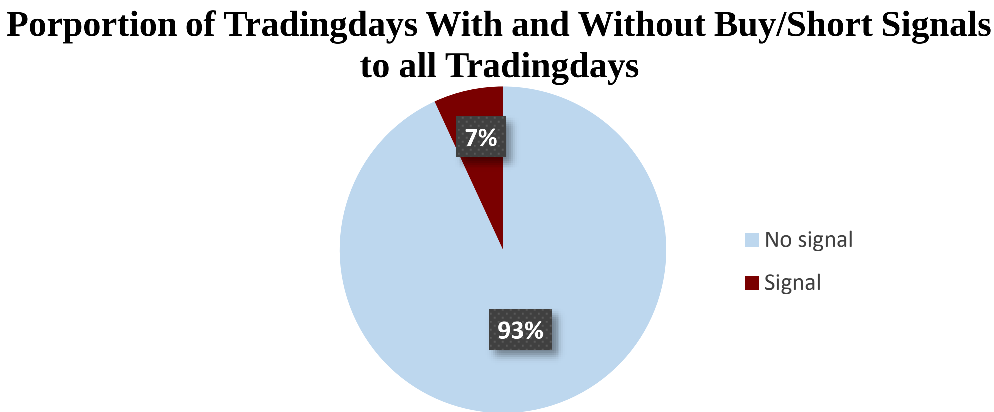


Figure 12: Proportion of trading days with a signal and without a signal to the total number of trading days recorded across all 29 stocks.

There are 17946 days of uptrend in the sample, 16003 days of downtrend and 25704 days of continuation (see Appendix Table 1) which means that the data set is fairly balanced with no clear overall bearish or bullish trend being discernable across all the data (see Figure 13). The results also show that a large proportion, 43% of the trading days recorded are continuation days.

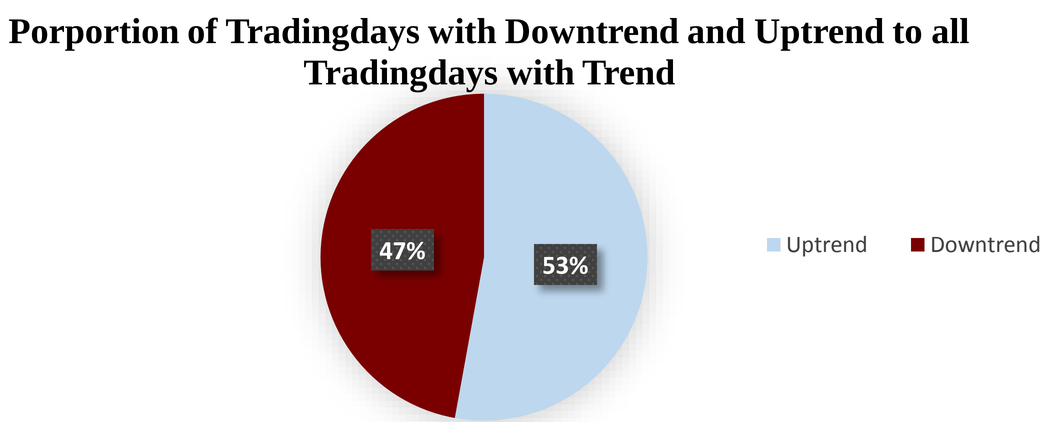


Figure 13: Proportion of trading days with downtrend and Uptrend to the total number of trading day's with trend across all 29 stocks.

For the 1882 bullish patterns identified, 964 accurately predict trend reversals and 912 predict a trend reversal that never occurs (see Appendix Table 2). Bullish patterns therefore have a 51% rate of success and a 48% rate of failure (see Figure 14.1). The statistical p-value for the bullish reversal patterns is 72% which is well above the critical 5% significance level (see Appendix Table 2).

The results are similar for the 2245 bearish patterns identified, with 1089 accurate predictors and 1139 false predictions (see Appendix Table 2), corresponding to a 49% rate success and 51% rate of failure (see figure 14.2). With a p-value of 63%, the null hypothesis that bearish patterns in aggregate do not predict trend reversals cannot be rejected (see Appendix Table 2). Therefore, neither the bullish nor bearish candlestick reversal patterns are in aggregate statistically significant reversal predictors.

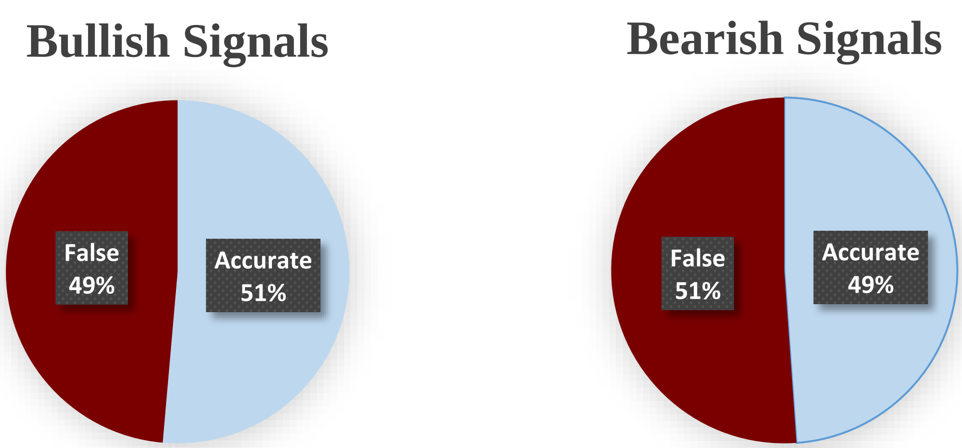


Figure 14.1 left (Bullish) and Figure 14.2 right (Bearish): The percentage of accurate and false reversal signals that the eight candlestick patterns have generated, for both bullish and bearish candlestick patterns.

The trend of non-significance continues when moving onto the results for the individual patterns reversal power. P-values, pattern count and success rates are presented in (Appendix Table 2). There is no evidence that any pattern works as a trend reversal pattern. The individual success and failure rates for each of the eight candlestick patterns is presented in Figure 15, and their total frequency is presented in Figure 16.

The Bullish Engulfing pattern is identified 697 times, it has a success rate of 51%, and is not significant with a p-value of 72%.

The Bearish Engulfing in the most common pattern being identified 909 times yet is only successful 47% percent of the time making it the worst predictor out of the patterns, it is unsurprisingly not a statistically significant predictor with a p-value of 84%.

The hammer, one of the supposedly most common patterns is only identified 223 times, it has a success rate of 51%, and is not a significant predictor with a p-value of 78%.

The Hanging Man which is also supposed to be one of the more common patterns is only identified 303 times, it has a success rate of 49% and a p-value of 46%.

The Piercing Lines is the rarest pattern only being identified 115 times, but it is also the most successful with an accurate prediction rate of 57%, its p-value is 16%.

The Dark Cloud Cover is the second rarest pattern, identified 129 times, it does however not enjoy the same success rate as its inverse the Piercing Lines with a measly success rate of 48%, the P-value of the Dark Cloud Cover pattern is 57%.

The Bullish Harami is found 847 times, has a success rate of 51% and a p-value of 63%.

The Bearish Harami, identified 904 times and successful 50% of the time is not significant with a p-value of 31%.

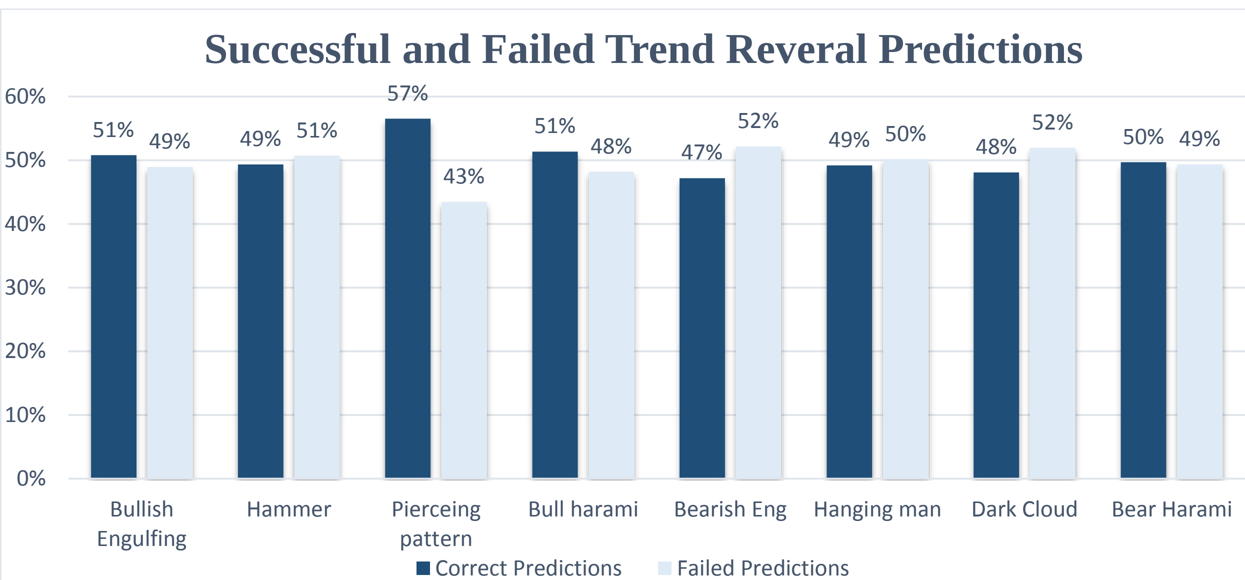


Figure 15: Presents rate of failure and success for all eight candlestick patterns, the correct predictions are defined by the candlestick patterns successfully reversing a trend according to Equation 4 for bullish patterns and Equation 5 for bearish patterns. The failures are defined by the candlestick appearing before a continuation of the previous trend defined by equation 5 for bullish patterns and Equation 4 for bearish patterns.

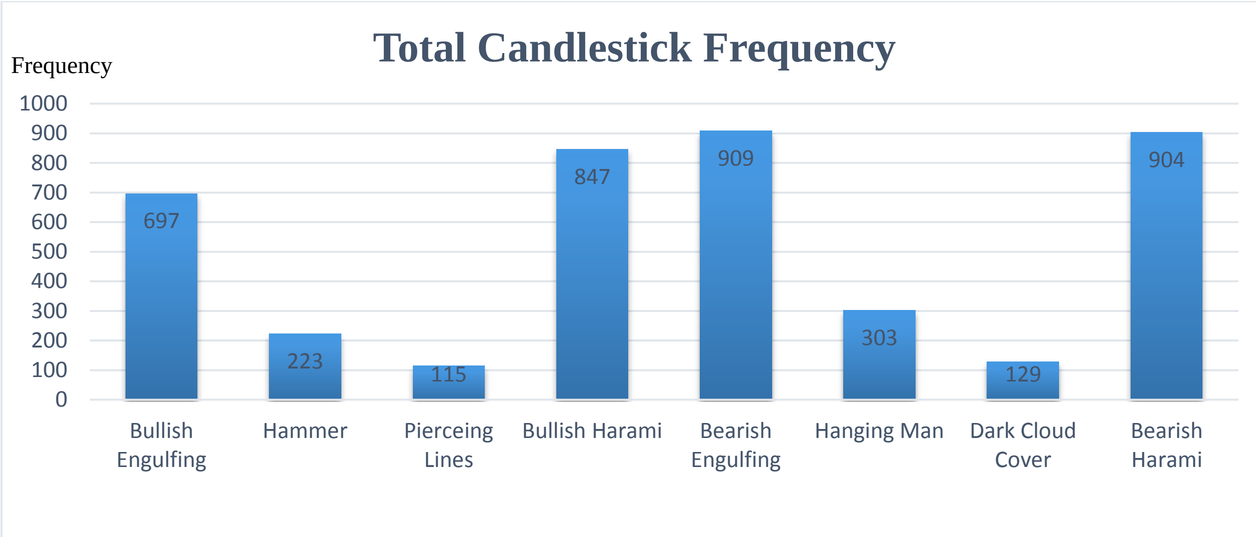


Figure 16: Shows the number of times a candlestick pattern has been identified across all trading days for all 29 stocks

5.2 Holding Period Return Results, All Stocks Grouped

This section presents the profitability results of 1 to 10 day holding periods for all patterns across all 29 stocks (see Table 2). The average returns are calculated for all stocks combined. The average returns are tested if they are significantly higher than zero. The average returns are calculated for each corresponding holding period and they are therefore not daily returns. As such, the returns are greater both in the negative and positive, the longer the holding period. The Average returns are also correlated to some extent, this is a result of all 10 holding period returns being calculated using the same buy and short signals.

The results although not statistically significant indicate that the returns are slightly more positive across the bullish patterns than the bearish ones. The Piercing Lines and Bullish Harami returns are especially positive while the Hanging Man and Bearish Engulfing patterns are shown to be the worst performing in terms of average return. Out of all 80 tests only 3 or 3.75% are significantly higher than zero at the 5 percent significance level (see Table 2). The only pattern which achieves significance is the Piercing Lines pattern, which is also the pattern that displayed the most success as a trend reversal predictor (see Figure 15).

Table 2: Are Candlestick Patterns Profitable Trading Signals

Presents the average return (return), the standard error (Error) and p-values for all 29 stocks. The null hypothesis is that the average returns are not different from zero and the alternate is that the average returns are greater than zero, degrees of freedom can be obtained in Appendix Table 2.

		Patterns							
Holding Period Days		Bullish Engulfing	The Hammer	Piercing Lines	Bullish Harami	Bearish Engulfing	Hanging Man	Dark Cloud	Bearish Harami
1	Return	-0,34%	0,11%	-0,7%	-0,01%	-0,04%	0,05%	-0,10%	0,08%
	Error	0,09%	0,17%	0,21%	0,07%	0,06%	0,10%	0,19%	0,06%
	p-value	(100%)	(24%)	(100%)	(57%)	(78%)	(31%)	(69%)	(8%)
2	Return	-0,10%	-0,18%	0,03%	-0,08%	-0,15%	-0,31%	-0,12%	0,00%
	Error	0,11%	0,24%	0,36%	0,11%	0,10%	0,16%	0,27%	0,09%
	p-value	(81%)	(78%)	(47%)	(76%)	(92%)	(97%)	(67%)	(48%)
3	Return	-0,10%	-0,50%	0,32%	0,05%	-0,18%	-0,18%	0,00%	-0,05%
	Error	0,15%	0,34%	0,38%	0,14%	0,12%	0,20%	0,34%	0,13%
	p-value	(76%)	(93%)	(20%)	(38%)	(94%)	(81%)	(50%)	(65%)
4	Return	-0,11%	-0,82%	**1,06%**	0,04%	-0,30%	-0,40%	0,05%	0,01%
	Error	0,18%	0,38%	**0,47%**	0,16%	0,14%	0,26%	0,41%	0,13%
	p-value	(73%)	(98%)	**(1%)**	(41%)	(99%)	(94%)	(46%)	(47%)
5	Return	-0,09%	-0,86%	**1,11%**	-0,17%	-0,32%	-0,66%	0,18%	0,04%
	Error	0,19%	0,40%	**0,51%**	0,19%	0,16%	0,34%	0,41%	0,14%
	p-value	(68%)	(98%)	**(2%)**	(81%)	(98%)	(97%)	(34%)	(39%)
6	Return	-0,11%	-0,63%	**1,26%**	-0,11%	-0,27%	-0,64%	-0,07%	-0,03%
	Error	0,20%	0,44%	**0,57%**	0,20%	0,17%	0,35%	0,45%	0,16%
	p-value	(71%)	(92%)	**(1%)**	(71%)	(94%)	(96%)	(56%)	(57%)
7	Return	-0,14%	-0,27%	0,78%	0,16%	-0,40%	-0,46%	-0,15%	-0,04%
	Error	0,22%	0,44%	0,58%	0,20%	0,19%	0,37%	0,42%	0,17%
	p-value	(74%)	(73%)	(9%)	(21%)	(98%)	(89%)	(64%)	(58%)
8	Return	0,07%	-0,32%	0,58%	0,23%	-0,49%	-0,68%	-0,47%	-0,07%
	Error	0,22%	0,44%	0,58%	0,20%	0,19%	0,37%	0,42%	0,17%
	p-value	(38%)	(74%)	(20%)	(14%)	(100%)	(96%)	(82%)	(65%)
9	Return	0,19%	-0,04%	0,77%	0,24%	-0,54%	-0,66%	-0,43%	-0,04%
	Error	0,24%	0,55%	0,65%	0,23%	0,21%	0,42%	0,51%	0,20%
	p-value	(22%)	(53%)	(12%)	(14%)	(99%)	(94%)	(80%)	(57%)
10	Return	0,11%	0,01%	0,76%	0,20%	-0,64%	-0,69%	-0,39%	-0,14%
	Error	0,25%	0,60%	0,64%	0,24%	0,21%	0,42%	0,48%	0,21%
	p-value	(33%)	(50%)	(12%)	(20%)	(100%)	(95%)	(79%)	(74%)

5.3 Bootstrapped Results, Individual Stocks

This section presents the p-value frequencies attained from comparing the average holding period trading returns for the individual stocks with those attained from the bootstrapped price-series-data. The 29 stocks generated average returns from 10 holding periods and 8 candlestick patterns resulting in 2320 average returns to be compared and therefore 2320 p-values. In total there are 50 statistically significant average holding period returns (see Table 3) which corresponds to a 2% rate of significance. All the significant returns are constrained to the Hammer, Hanging Man, Piercing Lines and Dark Cloud Cover patterns. There appears to be no difference in significance in terms of how long the holding period is, the significant results are spread randomly throughout the 1 to 10 day holding period range.

Table 3: Profitability of Candlesticks Pattern Analysis

Count of p-values for the bootstrapped holding period return tests for the 29 stocks. All stocks p-values are summed for each holding period. Price series data is generated using the GARCH-M model. The p-values for each holding period are counted as significant when the bootstrapped holding period return is greater than that of original stock less than five percent of the time.

Candlestick	Holding Period Days									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Bullish Patterns										
Engulfing	0	0	0	0	0	0	0	0	0	0
Hammer	3	3	0	1	1	1	1	2	2	3
Piercing Lines	0	1	2	1	1	1	1	1	1	1
Harami	0	0	0	0	0	0	0	0	0	0
Bearish Patterns										
Engulfing	0	0	0	0	0	0	0	0	0	0
Hanging	1	1	1	0	1	2	2	2	3	3
Dark Cloud	1	2	1	2	1	0	0	0	0	0
Harami	0	0	0	0	0	0	0	0	0	0

Table 4: Profitability of Candlesticks Pattern Analysis

Count of p-values for the bootstrapped holding period return tests for each of the 29 stocks. All ten holding periods p-values are summed for each stock. Price series data is generated using the GARCH-M model. The p-values for each holding period are counted as significant when the bootstrapped holding period return is greater than that of original stock less than five percent of the time.

Stock	Candlestick Pattern							
	Bullish Engulfing	Hammer	Piercing Lines	Bullish Harami	Bearish Engulfing	Hanging Man	Dark Cloud	Bearish Harami
Fingerprint Cards								
ASSA ABLOY								
Swedish Match								
SCA							1	
Kinnevik, Investment								
Investor								
Securitas						4	1	
Atlas Copco B		9						
Atlas Copco A							2	
AstraZeneca						5		
Handelsbanken						1		
Lundin Petroleum			9					
Electrolux								
Getinge						2		
H&M		2						
Skanska						1	3	
Boliden		1						
Swedbank								
Nordea Bank								
SKF								
Ericsson		2						
ABB						3		
SEB		3						
TeliaSonera								
Volvo								
TEL2 B								
Sandvik								
Nokia								
SSAB			1					
Total	0	17	10	0	0	16	7	0

6. Analysis

The objective of the study is to test the predictive power and profitability of eight candlestick reversal patterns in the short term. To determine these, three statistical tests have been applied to the empirical results, this chapter analyses the results from these three test.

6.1 Summary Statistics

As mentioned in the result section relatively few trading days with buy or short signals are identified in relation to the total amount of trading days with roughly one signal being identified for every 15 days. The relative rarity is likely caused by a number of factors, firstly, only eight out of many candlestick patterns are studied. Secondly the rigorous definitions of candlestick patterns utilized is likely to have severely reduced the number of signals. The definitions incorporate most of the constraints recommended by prominent candlestick literature authors, including requiring confirmation before a candlestick is verified. Thirdly, the use of a five-day moving average can be a contributing factor in reducing the number of patterns identified, a moving average with fewer days will result in a more variable trend which can possibly generate more signals.

The data has an overall positive price drift trend, with an increase in the 29 stock price index of 43% over the time period. Despite the increase, the proportion of days with uptrend and downtrend to all days with trend is only slightly skewed towards days with uptrend, with uptrend days being 6 percentage points more common. An interesting extension of this result is that the amount of bearish reversal patterns (2245) is larger than the amount of bullish reversal patterns (1882). Although a bit counterintuitive, this result is logical, for the bearish reversal patterns can only be found in an uptrend and the bullish patterns only found in a downtrend, and since there is a slight skew towards uptrend days, a slight skew towards bearish patterns should be evident.

6.2 Predictive Power

Moving on to the predictive power of the candlestick patterns, which is tested using t-test for the binominal distribution approximated to the normal distribution. The predictive power proves to be poor across all patterns, with success rates ranging from 48% at the lowest to 58% at the highest and an average of 51% for bullish patterns and 49% for bearish patterns. These are the kind of results that are expected in a market where the random walk model holds, any predictive pattern in a random walk would have a success rate of around 50% due to the returns fluctuating around a mean of zero.

The p-values reflect the poor predictive power, ranging from 16% at the lowest for the Piercing Lines to 84% at the highest for the Bullish Engulfing pattern, with all the patterns predictive power being far from the 5% of statistical significance.

The bullish patterns prove to be marginally better predictors than their bearish counterparts, with 3 out of 4 above the 50% mark in terms of success while the bearish patterns success rate ranges from 48% to 50%. It is emphasized however, that no pattern except the Piercing Lines shows any indications of having real predictive power. The marginally better predictive power attained by the bullish patterns can be a result of random chance.

The results clearly show that predicating trend reversals using the eight candlestick patterns tested is a futile endeavor. These results lend strong proof for the efficient market hypothesis and random walk model.

6.3 Profitability Across all Stocks

The average rate of return for all eight candlestick pattern and ten holding periods is with very few exceptions shown to be lower than is required given the standard error to be statistically significantly higher than zero. The only pattern shown to be significant is the Piercing Lines pattern which is statistically greater than zero for 3 out of 10 holding periods. This result has to be considered cautiously however, considering that the test has a 5% type I error risk and 3 out of 80 tests or 3.75% are shown be significant. Essentially the significant returns could be a result of random chance, when a test is performed enough times there will be outliers which lie many standard deviations from the mean simply due to random happenstance. Because of the fact that the Piercing Lines pattern is so rare, only being identified 115 times it is especially vulnerable to type I error. Although it cannot be said that this is the case with absolute certainty, the overall results do point towards the significance being the result of random chance.

A trading strategy does not have to be statistically significant to be economically viable, the 5% alpha is in truth, a rather arbitrary choice for significance. Putting statistical analysis aside, the Piercing Lines pattern shows some promise as a profitable technical analysis trading indicator. It has an average return of to 1.24% for a 5 day holding period, which when compounded to a yearly rate of return corresponds to 246%. Although this yearly compounded average return does not take the standard error of 0.57% into consideration, the yearly rate of return while considering the standard error is still highly likely to be positive. The same goes for the 10 day holding period, which although insignificant with a p-value of 12% still could be economically viable due to having an average return of 0.76% over a 10 day holding period with a standard error of 0.64%. The financial implications of the average holing period returns do however, need to be viewed with the same skepticism as the significant p-values for the Piercing Lines pattern.

No pattern except the Pricing lines shows any signs of being economically viable. All other patterns either have a negative average holding period return or a standard error which exceeds the average return, which means that an investor is likely to attain a rate of return which fluctuates around zero.

The poor results from the tests for profitability for all 29 stocks show that the hypothesis of the Swedish stock market being weakly efficient cannot be rejected. Furthermore the results indicate there are no price anomalies caused by the behavioral theories presented for the various candlestick patterns.

6.4 Profitability Individual Stocks – Bootstrapping

The bootstrapped results are similar to those attained when testing if the average holding period return is statistically significantly greater than zero for all stocks. For the bootstrapped price data comparison, 50 statistically significant average returns are found out of 2320 average returns, which corresponds to roughly 2.16% of the data being significant.

The process of looking at individual stocks drastically increases the likelihood of finding significant holding period returns, this is of course due to the fact that the more tests performed the greater the chance for random outliers in the original data causing type I errors. An abnormally high return for a single stock, pattern and holding period could very well outperform 95% of the bootstrapped average returns if it is in fact an outlier.

Looking at the individual stock's significant p-value count, it is interesting to note that the stocks which display a high percentage price change across the test period like Fingerprint Cards and Assa Abloy do not display a greater amount of significant results than do other stocks. The same applies to stocks that have very negative period price changes like SSAB or Nokia. This shows that stocks with large price shifts are not better suited to candlestick charting than any other type of stock.

The patterns which generated significant results for the bootstrapping series comparison are all patterns which are identified the fewest times in the original data. These of course being the Hammer, Hanging Man, Piecing Lines and Dark Cloud Cover patterns. This is expected, considering that these patterns are the ones for which outlying data points are given the most relative weight on the average returns. For the more frequent patterns, the average holding period return for individual stocks is likely to be a closer approximation of a hypothetical mean, with less weight given to outlying values.

For example, Lundin Petroleum stands for 9 out of the 10 significant p-values found for the Piercing Lines pattern. When examining the data further, we find that the pattern is only identified 4 times for that particular stock and is in this case a 100% successful predictor. Considering these facts, it seems obvious the stock's average holding period returns for the Piercing Lines should outperform those attained with the randomly generated price data series 95% of the time. Furthermore, the holding period return correlation which arises from using the same trading signals explains why the pattern is significant for 9 out of 10 holding periods.

This example clearly shows that it was a simple result of chance that generated such high returns for the Piecing Lines pattern when tested on Lundin Petroleum price-data. This is the weakness of studying individual stock holding period returns for candlestick patterns which are very rare. Examining Table 4, it is clear that the clustering of significant p-values to certain stocks and patterns, can be a result of random outliers like the one described for Lundin Petroleum. The example also illustrates the data-mining properties inherent in using 1 to 10 holding period returns, for eight patterns and 29 stocks. With the calculation of so many p-values, some are bound to have type I error.

With only 2.16% of the p-values being statistically significantly higher for the original stocks, the bootstrapping results are more robust than the profitability test for all stocks combined. As such, the results from bootstrapping lend proof for theory of the Swedish stock market being weakly efficient.

7. Conclusion

The purpose of the study is two-fold, to test if candlestick patterns can predicts future price movements and to ascertain if they can be used to gain excess returns over the short term. To this end, three separate statistical test, one for predictive power and two for profitability are carried out.

The results from the test determining the predicative power using the binomial distribution t-tests are the least ambiguous. They show that the null hypothesis stating that candlestick have no predicative power, cannot be rejected. In essence, none of the eight candlestick patterns appear to have any predicative power when used on Swedish stock data.

The second test is designed to determine if a technical trading strategy based on candlestick patterns when applied to all 29 stocks in aggregate, can produce holding period returns which are significantly greater than zero. The results show that the candlestick patterns have poor profitably when applied to the 29 OMXS stocks. Although some holding period returns are statistically greater than zero, it is not certain that these are not a result of random chance.

The third test, like the second is designed to determine if a technical trading strategy based on the eight candlesticks patterns can produce significant holding period returns. Unlike the second test however, the bootstrap test compares the holding period returns for each stock individually. Like the two previous tests, the bootstrapping test indicate that candlestick analysis holds no value in terms of profitability for investors on the Swedish stock market.

All three tests show that the application of a trading strategy based on candlestick patterns on the 29 OMXS30 stocks demonstrates neither profitably nor predicative power. The fact that all three tests show similar results lend proof to the theory of Swedish stock market being weakly efficient as well as to the random walk model. This study therefore joins a group of papers that have recently shown that candlesticks perform poorly on well developed markets such as the S&P500 or the DJIA.

The results also show that bullish patterns are marginally more profitable and display slightly higher predictive power than bearish patterns. Whether this is a result of the bullish patterns being better predictors or random chance is difficult to say. The holding periods are shown to be irrelevant in terms of which generate the higher daily returns. Large price-trends which occur over long periods of time have a no apparent effect on the profitability of candlestick pattern analysis. This is garnered from the fact that the stocks with the greatest percentage price changes over the test period performed no better than any other stock did.

Since measuring the success and failure of any pattern is an integral part of the study, it is noted, that the measuring tool for a pattern's success or failure as defined by Equation 4 and 5 is shown to be very powerful. This conclusion is based on the fact that the candlesticks which have a low rates of success as predictors also have a low average holding period returns. This is illustrated by the most successful trend reversal predictor, the Piercing Lines having the best and overall positive profitability results, while the least successful predictor the Bullish Engulfing pattern has a negative average return for all 10 holding periods.

Although the results fail to reject the hypothesis that the eight candlestick patterns hold no value for investors, it cannot be stated definitively that candlestick's as a group are useless to investors. Different patterns may very well have additional value, the eight candlesticks tested could even hold value to investors when combined with other technical indicators. Furthermore candlestick patterns may retain more predictive power when combined with other definitions of trend such as three-day moving average, exponential average or when trading volume is taken into account.

With the overall results in mind, the author cannot recommend the use of the eight tested candlestick patterns as technical indicators for short term trading on the Swedish stock market. Any such attempt is likely to result in negligible profitability or at worst, negative returns.

7.1 Criticism

Candlestick analysis is a broad category of technical analysis, the definitions and use of patterns is not uniform for all investors. Therefore there are always aspects of candlestick analysis which are not considered. The study is limited to only eight out of many possible candlestick patterns and it is therefore difficult to draw any broad conclusions about the profitability of candlestick pattern analysis in general.

The calculations are based on buying and selling at the exact opening and closing prices, something that in reality is hard to do consistently. This assumption can affect the holding period returns.

Since the study focuses exclusively on the most traded stocks, it excludes all illiquid equities that are traded in the Swedish stock market. Although in theory, technical analysis should perform worse while trading illiquid assets, their exclusion does affect the validity of the study to some extent.

7.2 Suggestions for Future Studies

Considering the limitations of the study in terms of moving averages, testing different moving averages and definitions of trend could be very interesting. Previous studies show that the three-day moving average employed by Lu (2012) as well as Caginalp and Laurent (1998) is the most successful at finding proof for candlestick pattern profitability. The three-day moving average does however require more recent research since it has not been tested in developed equity markets since Caginalp and Laurent (1998) studied the S&P500.

Another interesting aspect of technical analysis to examine is candlestick patterns in conjunction with other technical indicators such as the RSI or Fibonacci Sequences. Although adding indicators which are more vulnerable to data mining brings along certain risks such as data mining, these can mostly be eliminated with the use of a bootstrapping methodology. Furthermore, this area of candlestick charting has not been explored in any significant way and could therefore very well find hidden market inefficiencies.

Over the course of this study, it has become clear that the three-day and four-day patterns are purported to be better than two-day and single day patterns (Farley 2015). It would be interesting to see if this assumption is true.

The only pattern examined in the study which shows any promise is the Piercing Lines patterns. Since there is some ambiguity in the results regarding it's effectiveness, further research could be warranted.

8. Appendix

8.1 Appendix Tables

Appendix Table 1: Displays the summary statistics for the all 29 stocks.

Days of Uptrend	17946
Days of Downtrend	16003
Days of Continuation	25704
Total Trading Days	59653
Accurate Bull Signals	964
False Bull Signals	912
Continuation Signals, Bullish Patterns	6
Total Bull Signals	1882
Accurate Bear Signals	1089
False Bear Signals	1139
Continuation Signals, Bearish Patterns	17
Total Bear Signals	2245
Missed Uptrends	16982
Missed Downtrends	15091

Appendix Table 2: The Predictive Power of Candlestick Patterns

Displays the correct predictions, p-values and success rates for the eight candlestick patterns tested on all 29 stocks. The predictive power is tested using one sided t-tests

Candlestick Patterns	Total Patterns	Correct Predictions	Failed Predictions	Percentage of Correct Predictions	Percentage of Failed Predictions	σ	p-Value
Bullish Patterns							
Engulfing	697	354	341	51%	49%	13,19	72%
Hammer	223	110	113	49%	51%	7,46	78%
Pierceing Lines	115	65	50	57%	43%	5,36	16%
Harami	847	435	408	51%	48%	14,54	63%
All bullish	1882	964	912	51%	48%	21,69	72%
Bearish Patterns							
Engulfing	909	429	474	47%	52%	15,07	84%
Hanging Man	303	149	152	49%	50%	8,70	46%
Dark Cloud	129	62	67	48%	52%	5,68	57%
Harami	904	449	446	50%	49%	15,03	31%
All Bearish	2245	1089	1139	49%	51%	23,68	63%
Total	4127	2053	2051	50%	49%		

Appendix Table 3: Percentage Price Change for the Period

Recounts the percentage price change for each of the 29 stocks included in the study for the period from October 17, 2007 to December 31, 2015.

Stocks	Return
Fingerprint Cards	5882%
ASSA ABLOY	295%
Swedish Match	118%
Svenska Cellulosa	116%
Kinnevik, Investment	94%
Investor	94%
Securitas	92%
Atlas Copco B	89%
Atlas Copco A	86%
AstraZeneca	79%
Handelsbanken	69%
Lundin Petroleum	67%
Electrolux	47%
Getinge	46%
Hennes & Mauritz	44%
Skanska	27%
Boliden	15%
Swedbank	15%
Nordea Bank	11%
SKF	6%
Ericsson	-13%
ABB	-13%
SEB	-14%
TeliaSonera	-24%
Volvo	-33%
TEL2 B	-39%
Sandvik	-43%
Nokia	-75%
SSAB	-90%

8.2 Candlestick Constraints

The follow section outlines the constraints, for which O_t denotes the opening price on day t, H_t the highest price on day t, L_t the lowest price on day t and C_t the closing price for any day $t = 1,2 \dots n$.

The Hammer

Constraint Hammer: $A\ downtrend\ must\ be\ underway$

$C_2 > C_1$ (Confirmation)

Black candlestick:

$C_1 < O_1$

$C_1 - L_1 > 2 * (O_1 - C_1)$

$(H_1 - L_1)/10 > H_1 - O_1$

White candlestick

$C_1 > O_1$

$O_1 - L_1 > 2 * (C_1 - O_1)$

$(H_1 - L_1)/10 > H_1 - C_1$

The Hanging man

Constraint hanging Man: $An\ upptrend\ must\ be\ underway$

$C_2 < C_1$ (Confirmation)

Black candlestick:

$C_1 < O_1$

$C_1 - L_1 > 2 * (O_1 - C_1)$

$(H_1 - L_1)/10 > H_1 - O_1$

White candlestick

$C_1 > O_1$

$O_1 - L_1 > 2 * (C_1 - O_1)$

$(H_1 - L_1)/10 > H_1 - C_1$

Bullish Engulfing Pattern

Constraints: $A\ downtrend\ must\ be\ underway$

$O_1 > C_1$

$O_2 < C_2$

Option 1:

$O_2 \leq C_1$

$O_1 < C_2$

Option 2:

$O_2 < C_1$

$O_1 \leq C_2$

Bearish Engulfing Pattern

Constraints: $An\ upptrend\ must\ be\ underway$

$O_1 < C_1$

$O_2 > C_2$

Option 1:

$O_2 \geq C_1$
$O_1 > C_2$

Option 2:

$O_2 > C_1$
$O_1 \geq C_2$

The Piercing Lines

Constraints: $A\ downtrend\ must\ be\ underway$
$C_1 < O_1$
$C_2 > O_2$
$L_1 > O_2$
$C_2 \geq 0.5 * (O_1 + C_1)$

Dark-Cloud Cover

Constraints: $An\ upptrend\ must\ be\ underway$
$C_1 > O_1$
$C_2 < O_2$
$H_1 < O_2$
$C_2 \leq 0.5 * (O_1 + C_1)$

The Bullish Harami

Constraints: $A\ downtrend\ must\ be\ underway$
$C_1 < O_1$
$C_2 > O_2$

Option 1

$C_1 \leq O_2$
$C_2 < O_1$

Option 2

$C_1 < O_2$
$C_2 \leq O_1$

The Bearish Harami

Constraints: $An\ upptrend\ must\ be\ underway$
$C_1 > O_1$
$C_2 < O_2$

Option 1

$C_1 \geq O_2$
$C_2 > O_1$

Option 2

$C_1 > O_2$

$C_2 \geq O_1$

8.3 Excel Definitions

The formulas assume Column A has the Date, B has Open, C has High, D has Low, E has the Closing price. The formulas begin on line 10 (Today), line 9 (Yesterday) and line 8 (day before Yesterday) and, line 11 (tomorrow)

The Hammer

Excel:

$$= IF(OR(AND(G9 < D9; (G9 - F9) > 2 * (D9 - G9); (E9 - F9)/10 > (E9 - D9); G10 > G9; P8 = 1); AND(G9 > D9; (D9 - F9) > 2 * (G9 - D9); (E9 - F9)/10 > (E9 - G9); G10 > G9; P8 = 1)); 1; 0)$$

The Hanging Man

Excel:

$$= IF(OR(AND(G9 < D9; (G9 - F9) > 2 * (D9 - G9); (E9 - F9)/10 > (E9 - D9); G10 < G9; O8 = 1); AND(G9 > D9; (D9 - F9) > 2 * (G9 - D9); (E9 - F9)/10 > (E9 - G9); G10 < G9; O8 = 1)); 1; 0)$$

Bullish Engulfing

Excel:

$$= IF(OR(AND(D9 > G9; D10 < G10; D10 <= G9; D9 < G10; P9 = 1); AND(D9 > G9; D10 < G10; D10 < G9; D9 <= G10; P9 = 1)); 1; 0)$$

Bearish Engulfing

Excel:

$$= IF(OR(AND(D9 < G9; D10 > G10; D10 >= G9; D9 > G10; O9 = 1); AND(D9 < G9; D10 > G10; D10 > G9; D9 >= G10; O9 = 1)); 1; 0)$$

The Piercing lines

Excel:

$$= IF(AND(G9 < D9; D10 < F9; D9 > G10; G10 >= (0{,}5 * (D9 + G9)); P9 = 1); 1; 0)$$

Dark Cloud Cover

Excel:

$$= IF(AND(G9 > D9; D10 > E9; D9 < G10; G10 <= (0{,}5 * (D9 + G9)); O9 = 1); 1; 0)$$

The Bullish Harami

Excel:

$$= IF(OR(AND(D9 > G9; G10 > D10; G10 <= D9; G9 < D10; P9 = 1); AND(D9 > G9; G10 > D10; G10 < D9; G9 <= D10; P9 = 1)); 1; 0)$$

The Bearish Harami

Excel:

$$= IF(OR(AND(G9 > D9; D10 > G10; D10 <= G9; D9 < G10; O9 = 1); AND(G9 > D9; D10 > G10; D10 < G9; D9 <= G10; O9 = 1)); 1; 0)$$

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