

# Do Japanese Candlestick Patterns Help Identify Profitable Trading Opportunities? An Analysis on Selected Forex Markets 

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\text { هل تساعد نماذج الثموع اليابانية على إيجاد فرص تداول مربحة؟ }
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## By

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#### Abstract

Japanese candlestick charts were first introduced to the Western world in 1989 by Steve Nison. No one in the West got to know about the Japanese technical analysis before the first edition of his textbook, and no charting packages included them either prior to the first edition. Japanese candlestick patterns have become very popular since then. Japanese candlestick patterns are technical trading rules that are used to predict price directions based on the relationship between opening, high, low and closing prices. Currently many market participants are implementing Japanese candle patterns as part of their robust trading systems. This research examines the profitability of four bullish and four bearish Japanese candlestick reversal patterns in seven foreign exchange currencies which represent both advanced and emerging foreign currency markets. These currencies include AUD/USD, USD/CAD, EUR/USD, GBP/USD, USD/INR, USD/JPY and USD/ZAR. The sample covers a 12-year span of 3,129 observations. The statistical z score test is used to test the statistical significance of the returns at $5 \%$ level for seven holding periods. The RSI is used with three candle patterns to further filter the results. The findings show strong evidence of some profitable candlestick reversal patterns in foreign currency markets.


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## Chapter 1

## Introduction

## Chapter 1: Introduction

Foreign exchange markets have been the main target for most of the market participants to internationally trade, invest and hedge foreign currency risk exposure. The uniqueness of this kind of financial market is mainly due to its high liquidity, leverage, and geographical and time zone coverage. According to an article published by Bloomberg and based on information released by the Bank for International Settlements (BIS) in September 2012, foreign currency trading may have reached \$5 trillion a day, exceeding the highest level reached prior the collapse of Lehman Brothers in 2008. Though trading fell to approximately $\$ 4.7$ trillion a day in October, 2012, and likely to fall further, it is still remains the number-one financial market for all market participants. (Worrachate and Goodman, 2012) check

The global financial market place has evolved significantly during the last decade. Investment and hedging strategies have changed accordingly. Market participants have been exploring different strategies that would enable them to generate maximum returns with minimum risk. Investment fund managers and risk managers, for example, consult fundamental analysis, value investing strategy, technical analysis and any other possible tool they could add to their trading-strategies portfolio.

There are various tools that market participants use in foreign exchange markets, especially for spot foreign currency trading. This is mainly because a large portion of investment activity in the foreign exchange market is conducted through spot trading. The spot foreign exchange market has been closely examined to look for profitable opportunities and find the best investment and trading strategies. Both fundamental analysis and technical analysis have been used to predict price movements though they differ significantly. Fundamental analysts study the cause of the price movements, whereas technical analysts examine the effect (Murphy, 1999). Recently, many investment managers and individual traders integrate fundamental and technical
analysis in their investing and trading strategies, which has been found very rewarding. They use fundamental analysis for long-term investment strategies, and use technical analysis for short-term trading activities. According to a survey conducted by Taylor and Allen (1992), 90 per cent of foreign exchange traders in London use price charts as technical trading rules for short-term trading.

Though technical analysis is used widely, some academicians and market followers still believe that returns are not predictable and that technical analysis cannot be used to forecast prices. Although there is a challenge of turning technical analysis into a science, a lot of studies have been conducted to examine the profitability of technical trading rules statistically in financial markets. Considering the information above, this research attempts to examine the profitability of using technical trading rules to predict price movements of selected foreign currencies. These technical rules are called Japanese candlestick patterns that were originally used by Munehisa Homma who made a fortune from trading them in the rice market in 1700s (Nison, 2001). Details of different Japanese candlestick trading patterns are discussed later in the research. The next sections include the rational of the research, the research problems, the objectives of the research, and the null hypotheses, followed the limitations of the research.

### 1.1 Rational of the Research

Foreign exchange markets are one of the main targets for most of the market participants as they are considered the largest financial markets in the world. Market participants who access foreign exchange market include traders, fund managers, pension fund managers, banks, corporate and other financial institutions. Foreign exchange markets do not only provide trading and investment opportunities, but they also offer risk managers great opportunities to trade as hedging activities that would enable them to mitigate the foreign exchange risk exposure resulting from uncertainty in high price volatility. This research is important because it can serve different financial
institutions and traders for investment and hedging decision making, and academicians who are looking for tested trading results.

This research is also important because it examines major foreign exchange currencies that represent advanced and emerging economies which provide different trading opportunities especially after the recent financial meltdown that started in 2007. Emerging markets have become one of the main targets for investors as they have showed potential for high returns when compared with other advanced economies. Despite the fact that emerging markets may still present a high risk of political uncertainly, local infrastructure issues and illiquidity, they still provide good opportunities for outside investors. Emerging markets have been experiencing faster economic growth, measured by their GDP, though still partially impacted by the slow global economic growth resulted from the Euro Zone debt crisis and the US fiscal cliff fears.

The foreign exchange currencies include five advanced market currencies and two emerging market currencies against the US dollar: the Australian dollar, the British pound, the Canadian dollar, the Euro, the Japanese yen, the South African rand and Indian rupee, respectively. There are four main reasons to select these currencies: 1) they are highly liquid; 2) they are considered trade, commodity and hedging currencies; 3) they reflect both advanced and emerging foreign markets; 4) they represent different economies and geographical regions and 5) the data period used in the analysis is long and very recent. All these factors together make this research interesting and attractive.

### 1.2 Research Problems

Based on the traditional finance research on financial market efficiency, technical trading rules cannot be used to beat the markets and generate excess returns. It is considered that financial markets are efficient and their prices consistently and fully reflect available information (Fama, 1970; Samuelson, 1995). However, there are a lot of studies that have been conducted to re-test markets efficiency. Some empirical
researches find that financial markets, including foreign exchange markets, are efficient, and that technical trading rules cannot be used to forecast future price movements, supporting the weak form of the Efficient Market Hypothesis (EMH).

On the other hand, other empirical studies reject the concept of the first form of the EMH and find that technical trading rules can be profitable indeed. These findings of successful trading rules have been documented empirically using different sample data of different financial markets, across different time periods and in different regions. The findings show that some financial markets have been found informationally inefficient. The foreign exchange market efficiency has also been examined, and strong evidence of profitable technical trading rules, has been found.

### 1.3 Objectives of the Research

The main objectives of the research are as follow:

- To statistically examine the predictive power of four bullish and four bearish Japanese candlestick patterns to forecast price movements or returns in seven selected foreign exchange currencies.
- To contribute to the literature by providing an additional research in the field of technical analysis through examining the profitability of Japanese candlestick patterns, and with results that either support or reject the weak form of the EMH.
- To raise awareness of profitable trading strategies in major, commodity and emerging market foreign currencies that can provide good trading opportunities for market participants, and can help them make investment and hedging decisions.


### 1.4 Null Hypothesis

To test the weak form of the EMH and examine the predictive power of technical trading
rules of selected Japanese candle reversal patterns in foreign currencies, the following null hypotheses are tested:

1. $\mathrm{H}_{0}$ : All Japanese candlestick reversal patterns cannot be used to forecast foreign currency price movements.
Ha: Japanese candlestick reversal patterns can be used to forecast foreign currency price movement.
2. $\mathrm{H}_{0}$ : Foreign exchange markets are efficient.

Ha: Foreign exchange markets are inefficient.

### 1.5 Limitations of the Research

There are two main limitations encountered while working on the methodology. The first one is the inability to include USD/CNY in the sample as an emerging market foreign currency; this is due to the missing data of high and low rates from the beginning of the sample period till the end of August, 2005, downloaded from Thomson Reuters. This currency has received a lot of attention recently and many market participants have shown interest in it through diversifying their portfolios; emerging markets have shown promising profitable opportunities especially after the last financial crisis, Euro Zone debt issue and the US fiscal cliff threat. However, since this research addresses emerging market foreign currencies as well, USD/ZAR is selected as a replacement for the Chinese Yuan. Many financial institutions, especially airlines and logistics firms have profits or repatriation in USD/ZAR, adding another reason to include it in the sample. The second limitation is the lack of solid knowledge in programming to transform the subjectivity of different variations of Japanese candlestick patterns into an objective software or model that would both identify the patterns and test them statistically. This limitation is partially addressed through using excel formulas and statistical tests and find the identified ones on real charts to ensure the patterns are properly reflected.

The rest of the research paper is organized as follows: Chapter two introduces the Efficient Market Hypothesis (EMH) in its three forms; Chapter three discusses the difference between fundamental analysis and technical analysis as well as subjective technical analysis versus objective technical analysis; Chapter four includes an explanation of terms and concepts and a survey of literature reviews, followed by a summary of reviews, comments and criticism; Chapter five introduces the technical trading rules of the Japanese candlestick patterns and the Relative Strength Index (RSI); Chapter six explains the methodology that includes the sample data and the analytical tools used to test the null hypotheses; Chapter seven includes the discussion of the study analysis; Chapter eight summarizes the findings and recommendations and finally Chapter nine includes the conclusion, followed by bibliography and appendices.

## Chapter 2

## Efficient Market

## Hypothesis (EMH)

## Chapter 2: Efficient Market Hypothesis (EMH)

Markets with prices that consistently and fully reflect available information are called efficient. This is the building block of the Efficient Market Hypothesis (EMH) that was brought up by Fama and was further developed by him in 1970. Fama (1970) divides the EMH into three forms of market efficiencies, depending on relevant information that stock prices adjust to. These subsets include the weak form, the semi-strong form and the strong form.

The weak form states that future prices cannot be predicted by examining historical prices and used to generate excess returns. Therefore, investment strategies and decisions cannot be made based on technical analysis. This means that security prices do not have any particular pattern and future price movements are subject to information that is not part of price series. Thus, security prices follow a random walk rather than particular historical patterns, and that market participants cannot profit from market inefficiencies.

The semi-strong form discusses the ability of stock prices to adjust efficiently to information that is available to the public, such as different announcements of annual profits and stock splits. It states that stock prices adjust to available new information to the public very fast and objectively. Thus, market participants cannot earn excess returns through trading that kind of information. This form states that both fundamental analysis and technical analysis cannot be used to beat the market and make superior returns.

Finally, the strong form of the EMH is concerned with certain individuals or groups that might have monopolistic access to such private information. This form implies that stock prices represent both public and private information. Thus, market participants will not be able to use any kind of information to generate excess returns.

In brief, the EMH implies that the reaction of market participants is random. Thus, market prices cannot be exploited to consistently generate any excess returns, particularly when accounting for the transaction costs of spreads and commissions. Market participants can be wrong, but the markets are always right.

Mixed empirical evidence exists in the literature that either support or reject the EMH. Although the EMH is supported by some academicians and market participants, it has also been disputed by many investors and researchers both empirically and theoretically. One of the important studies in the literature is the research conducted by Lo and Mackinlay (1989) on the Random Walk Theory. They examine the theory using weekly stock returns for the period from 1962 and 1985. The results strongly reject the Random Walk model for the whole sample.

The EMH has started to lose some weight. Interestingly, even leading proponents of the theory have started to divert in their belief in the validity of the random walk concept. Burton Malkiel, a famous American economist and the author of "A Random Walk Down Wall Street", who has been a big supportive of the EMH, has recently pointed out that some emerging markets like China, particularly Shanghai and Shenzhen financial markets, have been found inefficient. (Malkiel, Mei and Yang, 2006)

Some EMH proponents still argue that luck is the main reason behind some successful traders. However, being the most successful investor of the 20th century ranked among the world's wealthiest people, Warren Buffett argued against them and stated that the number of the large part of successful investors among the best money managers just dispute the argument above. Warren Buffet is among other super-investors who have managed to beat index funds many times. More than twenty seven years ago, Buffet mentioned that there were nine investors who invested in different firms; they had made more profits than what index funds did. They were able to beat the market by a big margin and performed very well even when the market was not attractive. (Buffett, 1984)

The latest finical crisis that started in 2007 has also renewed the criticism of the EMH. Jeremy Grantham, one of the highly respected financial strategists and investors, stated that the EMH is responsible for the current financial crisis. He said that the belief in the model has made financial leaders underestimate the dangerous implications of asset bubbles, such as the dot-com and housing bubbles, as stock prices were not irrational after all. He was quoted that NASDAQ would correct 75 per cent which does not exist in an efficient market as this would indicate that growing shares have turned more valuable. (Nocera, 2009)

The EMH has become controversial as evidence of substantial and lasting inefficiencies are observed, opening the door to direct and indirect criticism of all the three forms. The history of many financial markets records various cases with fund and other investments mangers showing outstanding performance and being able to beat the market consistently. Though the weak form states stock price movements are random or trendless, given unchanged fundamental information, many researchers have found evidence that stock markets and other financial markets do trend. They have also found that there is an existence of a correlation between trending and length of the time frame, collecting another evidence to reject the weak form of the hypothesis. Other studies have revealed that market participants can make abnormal returns by trading stock dividend and other announcements including major economic indicators and central banks interventions in the foreign exchange markets. Moreover, there are different financial anomalies that have been found in the markets and have enabled market investors to generate excess returns. These findings clearly reject the second form of the EMH. Similarly, the last form of the EMH can be easily challenged; one can argue that the excess return made through insider trading is a good example that simply disputes the strong form of the EMH.

The key debate about making abnormal returns and beating the market "consistently" by the proponents of the EMH will always be challenged by the strategies that result in making excess returns from trading technical trading rules, dividend announcement and
financial anomalies and executing insider trading. EMH proponents do not only have to justify how the above can simply reject the three forms of the EMH, but also explain the rational of such asset bubbles and their subsequent collapse. This research addresses the weak form of the EMH and examines the predictive power of selected Japanese candle reversal patterns as technical trading rules.

## Chapter 3

## Fundamental Analysis (FA) Vs Technical Analysis (TA)

## Chapter (3): Fundamental Analysis (FA) Vs Technical Analysis (TA)

Fundamental analysis and technical analysis are the two main approaches used by funds and other finance managers to analyse a security value and monitor risk and return tradeoffs while managing portfolios. There has always been a debate on which approach is superior to the other one and whether they substitute or complement each other.

Fundamental analysts focus on security market price and its true values. In order to invest in a stock or any other financial security, fundamental analysts study the economic factors of supply and demand, which affect the price directions. In particular, they assess all the factors that can affect the security market price in order to determine the intrinsic value of that security (Murphy, 1999). Fundamentalists look at the book value and examine financial statements and use price-to-book ratio. Earnings are another key factor that reflects the income power of a stock, using the price-earnings ratio. These two ratios are important for many fundamentalists because they show the deviation of the shares from asset backing of the security. The second ratio of price to earnings shows the deviation of the shares from the earning power of the stock (Raymond, 12). So, if the intrinsic value is below the market price, this means that the security is overpriced and should be liquidated. However, if the intrinsic value is above the market the price, it means that the security is underpriced and it should be added to the portfolio.

On the other hand, technical analysts believe that fundamental factors of securities are discounted and accounted for in the market price itself. Technical analysts study the market action as they believe that prices move in trends and that history patterns in financial markets repeat themselves. They forecast future market prices through examining short-, intermediate- and long-term trend directions, price patterns, technical
oscillators, time cycles, inter-market analysis and other technical tools (Murphy, 1999). As for the fundamental analysis, the technical analysis has also attracted a lot of investors, practitioners and academicians. The recognition of historical price movements to forecast future directions goes back to a number of editorials written by Charles Dow published between 1900 and 1902 in Wall Street Journal. These publications have encouraged further research and revisit of existing literature to assess the profitability of technical analysis and test the validity of the EMH.

Nowadays, technical analysis is widely used by many big institutional investors and other market participants, in their trading and investing strategies. The power of mathematics of artificial intelligence as well as price pattern identification software has been growing so drastically (Raymond, 2012). The globalization and the integration of different financial markets worldwide along with the advanced technology have enabled technical analysts to adjust their trading strategies very rapidly when there are major movements. These speedy tools are not available for the fundamentalists.

One could argue against each analysis performance. Many big fund managers are fundamentalists, such as Warren Buffet, John Templeton, Peter Lynch and Liu Yang. They follow value investing and fundamental analysis in their investment decisions. Warren Buffett avoided IT shares prior the IT bubble at the time investors were laughing at him. At that time, he acknowledged he should get a "D" grade for his portfolio performance. Another credit that goes for the value investing approach is when John Templeton went for short positions on IT IPO when other traders were celebrating their big returns. In these cases, both fundamental and value investing analysis won at the end. However, a lot of fundamental analysts were caught by surprise in the sudden collapse in some stock markets. In 2011, Hong Kong stock market collapsed when the market PE was not expensive at all at that time. That is one of the situations when the fundamentalists fell in the value trap (Raymond, 2012). This brings the importance of technical analysis in spotting trend changes and potential reversals well ahead.

A lot of studies have been conducted to examine the ability of fundamental and technical analyses to assist funds and risk mangers to make correct decisions. Evidence of the profitability of technical analysis is explored in details in the literature review section. Other studies have gone further by examining the ability of integrating both analyses to optimize and further fine-tune investment and risk management strategies. Bettman, Sault and Welch (2006) propose an equity valuation model which integrates both analysis. Their sample includes US listed firms from January, 1983 to December, 2002. The results confirm that each analysis performs well when applied separately. However, the authors find that the integration of fundamental and technical analysis produces superior results. Thus, the finding confirms the nature of both analyses as complements rather than substitutes. Cooper (2011) also provides a simple framework that integrates both technical and fundamental analyses. His paper is expository in nature and explains the concepts without any mathematical evidence. It addresses the challenges of integrating technical and fundamental analyses in an optimum manner. It opens the door for practitioners and academicians to use the ideas in their testing models and explore the integration of both analyses in the future.

The literature shows evidence of a growing success of using technical and fundamental analyses as complements in the trading strategy and investment decisions. In fact, both analyses forecasting the market attempt to resolve the same issue of determining future price directions. The fundamental analyst examines the cause of the market direction, whereas the technical analyst studies the effect. At the start of major market moves, usually fundamental analysts are not able to explain what the market tends to do. This is the market stage when the two approaches fail to agree with each other. However, at some stage later, the two approaches do come back into sync, but not early enough for the trader to react. Another explanation for the discrepancies between the two is that market price movements tend to lead fundamentals. Since the known fundamentals have already been accounted for in the market, prices are currently responding to unfamiliar fundamentals. History records that some of the major bull and bear markets have started with little or zero perceived change in the fundamentals. At the time these
changes became familiar, the fresh trend is already in place. With the passage of time, technical analysts can develop growing confidence in their price chart signals and they become among the minority who can spot a change in trend directions. They know at some stage that the reasons for that trend reversal will become known to others.

Most analysts categorize themselves as either chartists or fundamentalists, but in reallife situations, there is an overlap. A lot of fundamental analysts have some basics about chart and trend analysis. Similarly, many chartists are aware of some important fundamentals. The main challenge is that sometimes price charts and fundamentals conflict with each other. (Murphy, 1999)

Last but not least, if a trader has a choice between the two approaches, the choice would logically be the technical analysis. By default, technical analysis includes the fundamentals. If the fundamentals are accounted for in the market price, it makes less sense to study those fundamentals. In other words, chart analysis has become a shortcut of fundamental or value investing analysis. Given the explanation above, it makes sense that one would depend on technical analysis in trading or investment decisions. It is doubtful that anyone can depend solely on fundamentals, ignoring the timing advantage of the technical analysis (Murphy, 1999). The explored literature in the literature review chapter represents different studies that examine the predictive power of using technical analysis in financial markets, with a focus on foreign currency markets.

Technical analysis is further divided into subjective technical analysis and objective technical analysis, introduced in the next section.

### 3.1 Subjective Analysis Vs Objective Analysis

Technical analysis can be classified into two categories: subjective and objective technical analysis (TA). Subjective TA refers to methods and patterns of analysis that cannot be clearly defined. This leads to the conclusion that technical analysts are open to personal views and interpretations when they use their technical trading rules. This means that it is possible for different analysts using the same method of same data sets, to have different findings. Thus, subjective trading rules cannot be tested and they are exempted from empirical examinations. Examples of subjective TA can include Gann Lines, trend channels, price chart patterns and divergences. (Aronson, 2007)

On the other hand, objective TA is clearly defined. When an objective trading rule is applied on a market data set, its signals are very clear and there is no room for ambiguity. This helps simulating technical methods on different historical data and identifying their performance level accuracy. In other words, it allows back testing. Thus, any objective method can be repeatable; it enables technical analysts and academicians to re-test previous findings of profitable technical trading rules and perhaps refute current statistical evidence. Examples of objective TA include moving average crosses. . (Aronson, 2007)

In a nutshell, one can distinguish between subjective and objective TA through using the programmability criterion; that is, a method is considered objective only if it can be implemented in a computer programme that can generate clear market positions. Any other technical trading methods that cannot be programmed become subjective by default. Subjective TA can be eliminated either through a shift into objective methods or rejection. (Aronson, 2007)

Aronson (2007) classifies TA into four main categories: 1) subjective TA, 2) objective TA with unidentified statistical significance, 3) objective TA that does not have statistical
significance and 3) objective TA of statistical significance. The first category refers to analysis methods that cannot be implemented into a programmed algorithm and be back tested, whereas the other three categories fall under objective methods. To explain further, the second category includes the methods that have been tested, but their findings have not been examined for statistical significance. The third category is considered useless; even though the values have been back tested and evaluated with statistical methods, they have been found of no value whether individually or when used in combination with other technical trading rules. Most of objective technical trading rules fall under this category. This is due to the complexity and randomness of the financial markets that make it difficult to predict. The fourth and the last category includes the objective methods that can be back tested and produce statistically and economically significant results. Some individual objective methods are useful; however since financial markets are very complex and random, rules will have more value if they are combined with other trading rules. (Aronson, 2007)

It has been very challenging not only to move TA to a science, which is transforming subjective TA into objective TA, but also to convince analysts who have been very proud of their technical trading rules, of the importance of the statistical significance tests and results. A good example in the literature that attempts to transform subjective TA into objective TA is done by Chang and Osler (1999). They objectify the price pattern of head and shoulders after facing a lot of problems. Among the main challenge faced is setting up the pattern parameters as in reality the pattern does depart from the ideal one. The authors decide to define objective rules that could discriminate valid from invalid head-and-shoulder patterns. These objective rules include percentage filters known as an Alexander filter, similar to a zigzag indicator that can identify peaks and troughs. They further develop innovative approaches that could qualify the pattern, such as vertical and horizontal symmetry and the time taken to form the pattern. (Aronson, 2007)

There are a lot of valid attempts that have been observed in the literature. The literature review section provides various studies that attempt to test different trading rules statistically.

## Chapter 4

## Literature Review

## Chapter (4): Literature Review

This chapter is divided into two main parts: explanations of terms and concepts found later in the literature reviews and a survey of literature reviews.

### 4.1 Explanation of Terms and Concepts:

- Bootstrap is a method that derives a sampling distribution of the test statistic through re-sampling with substitution from an original sample. (Aronson, 2007)
- Data mining is the process of searching for patterns, models and predictive rules in large data. (Aronson, 2007)
- Data mining bias is the expected variation, obtained by different experiments, between the observed performance of the best observed performance and its expected performance. (Aronson, 2007)
- Head and shoulder and double top price patterns are pictures appear on price charts that can be used to predict price movements.
- Japanese candlestick patterns are formations that are derived from open, high, low and close prices; they can be of one-day or more that have reversal and continuation predictive power.
- Monte Carlo simulation is a common method used to solve mathematical issues through random sampling in order to test the statistical significance of backtested data. (Aronson, 2007)
- NOVA is a statistical test that tests the difference in mean returns between multiple groups.


### 4.2 Survey of Literature Reviews

Over the past three decades, researchers have provided good evidence that the foreign exchange markets are inefficient, disputing the Random Walk Theory and the EMH. There is trustworthy evidence that simple technical rules or a combination or trading rules applied by a wide range of market participants, have proven to have predictive power of security prices. Thus, the reality that simple trading rules generate abnormal large returns in financial markets indicates a serious challenge to the traditional market hypotheses. To test the predictive power of technical analysis over different time frames and data samples, researchers have examined various financial markets of stocks, foreign exchange, bonds and commodities. Some findings show strong evidence of profitable technical trading rules, whereas others show poor or no evidence.

This section explores different studies that examine the profitability of various technical trading rules in different financial markets. More attention is given to the technical trading strategies of Japanese candlestick patterns and samples covering foreign currency markets where possible. The literature reviews focus primarily on the outcomes of applying technical analysis and its predictive value of future price movements. The literature survey is divided into four main streams: the first part covers the studies done in the stock and foreign exchange markets that show evidence of profitable technical trading rules; the second part covers the researches that use technical analysis in presence of central bank interventions. The third part reviews studies that apply Japanese candlestick trading rules. The fourth part includes the studies that find poor or no evidence of profitable technical trading rules. Questionnaire surveys on the application of technical analysis in trading decisions are also included in the literature. Each part reviews the literature chronologically from the oldest to the most recent ones to reflect the development that has been made since early 1980s.

Examining the profitability of technical analysis in financial markets has started very early. Longworth (1981) uses CAD/USD spot and forward rates from July 1970 to

October 1976. He finds that forward rates can be predicted using spot reference rates, concluding that markets are inefficient.

Brock, Lakonishok and LeBaron (1992) examine two simple, common trading rules: moving averages and range breakouts in the DJIA, from 1897 to 1986. Having applied a standard statistical analysis of the bootstrap method, the results reveal strong evidence of the technical trading strategies applied. The buy signals are found to constantly produce higher returns than sell signals. Also, the returns following buy signals are less volatile compared with the returns generated by sell signals.

Levich and Thomas (1994) examine the impact of technical trading strategies in the foreign exchange market by using futures contracts of a 15 -year time span. Their data sample covers the years from 1976 to 1990. After applying bootstrap methodology, and a statistical approach, thousands of new exchange rate series are randomly generated; each tested series' profitability is examined using a technical analysis approach. The empirical results of profit significance in both original series and randomly generated series are compared. The findings reveal that technical trading systems are significantly profitable. Although some profits declined during the five years of 1986-90, on an average, the profiles are found still positive and significant in some periods. Thus, these results provide evidence of profitability and statistical evidence of how technical trading systems are profitable in the foreign exchange market.

Gencay (1997) also finds strong evidence of profitable simple technical trading rules in daily Dow Jones Industrial Average Index. Having examined linear and nonlinear predictability of stock market return using historical buy and sell signals of the moving average rules, the result shows evidence of nonlinear predictability in the US stock markets, supporting the results found by Brock, Lakonishok and LeBaron (1992).

Osler (2000) examines the technical trading rules of support and resistance levels provided by six foreign exchange trading companies. The data sample covers the
period from 1996 to 1998. The statistical test of the bootstrap technique is used. The results show that signals are very successful in forecasting trend interruptions or reversals. The findings also show that some companies are more accurate in indentifying turning points in exchange rate trends. Overall, the prediction in USD/JPY and GBP/USD rates are more accurate than the prediction in DM/USD. Also, it is found that the predictive power of the support-resistance levels tend to last five working days at least once the levels are published to the public.

Osker (2003) examines clustering of foreign currency stop-loss orders as well as takeprofit orders as they are considered main orders when placing trading orders. His data covers 9,655 orders with a total of more than $\$ 55$ billion, from August 1, 1999, to April 11, 2000. His sample covers three foreign currencies: USD/JPY, EUR/USD and GBP/USD. He uses the crowded orders to provide an explanation for two common predictions of technical analysis. First, trends are likely to reverse directions at support and resistance areas. Second, trends are likely to move faster after prices penetrate such levels. He finds that take-profit orders gather at round numbers, explaining the first profit forecasting, whereas stop-loss orders concentrate heavily just after round numbers; this explains the reason behind the second forecasting. These findings are obtained based on the closing rates of both orders placed at the famous dealing bank of National Westminster. The order clustering phenomenon is due to different common reasons; round numbers are easy to remember and to place orders at as they are the first to come to anyone's mind. The final results show that technical trading rules can be profitable for market participants.

Omrane and Oppens (2004) use other technical trading strategies. They examine the presence of price chart patterns in intra-day EUR//USD, using both close and high-low prices. They search for 12 chart patterns and study them, based on the two criteria of profitability and predictability. Using the statistical methodology of Monte Carlo simulation to calculate results' statistical significance, the authors find evidence of chart
patterns in the foreign exchange market. The results reveal that more than 50 per cent of the charts that are identified, has high predictability.

Similarly, Shik and Chong (2007) also find technical trading rules profitable in foreign exchange markets. They apply moving averages and Relative Strength Index (RSI) using daily rates of six foreign currencies. They find that the profitability of using moving averages is obvious even though currencies belong to various economic areas.

In their paper, Lento and Gradojevic (2007) examine the profitability of technical trading rules by assessing their ability to outperform the trading strategy of buy and hold. The sample covers S\&P/TSX 300 Index, NASDAQ Composite Index, Dow Jones Industrial Average Index and CAD/USD spot exchange rate, from May 1995 to December 1994. The trading strategies include moving average cross rules, Bollinger Bands, filter rules and breakout rules of trading ranges. After accounting for the transaction costs, excess returns are generated by moving average cross-over rules and trading range break-out rules for the S\&P/TSX 300 Index, NASDAQ Composite Index and the CAD/USD spot exchange rate. Filter rules also earn excess returns when applied on the CAD/USD spot exchange rate. The bootstrap methodology is used to determine the statistical significance of the results. The profitability of the technical trading rules is further enhanced with a combined signal approach. The results show that a combined single strategy does outperform the buy-and-hold trading strategy even after accounting for transaction costs.

Park and Scott (2007), re-visit the historical testing measures of the profitability of technical analysis in the empirical literature; both early (1960-1987) and modern (19882004). Early studies show that technical trading rules are profitable in foreign exchange markets and futures markets only, but not in the stock markets. Modern studies, however, reveal that technical trading rules constantly generate economic profits in different markets. It is worth to mention that although strong evidence of the profitability of technical analysis is found in early studies, many empirical researches faced a lot of
problems in their tests, such as data snooping, selection of trading strategies and estimation of transaction cost. Early studies are characterized with different limitations in their tests, application of very few trading strategies, ignorance of trading rules risk and statistical significance of returns, absence of parameter optimization, out-of-sample verification and less attention to data snooping problems. On the other hand, modern studies show an overall improvement; earlier limitations encountered in the early studies, have been reduced; the number of trading rules used for testing has been increased; risk of trading strategies has been given high attention; both conventional statistical tests and sophisticated bootstrap methods have been applied with an emphasis on trading rule optimization as well as out-of-sample verification. Also, other empirical factors, such as order flows clustering, interventions of central banks and unstable market inefficiencies have been introduced as an explanation of technical trading returns. Final results of the study reveal that out of total modern studies of 95, 56 studies find technical analysis profitable in trading; 20 show negative results and 19 find mixed results.

Though difficult to explain how technical trading strategies of price patterns might be profitable, Friesen, Weller and Dunham (2007) provide a modal that shows evidence of how such price pattern trading rules can be profitable in the US stock markets. The data covers a six-year period from January 1999 to December 2005. The researchers highlight the significance of confirmation bias. Traders who obtain data and trade on that information are likely to bias their reading of subsequent information towards the direction of their initial view. This generates autocorrelations and price patterns that can forecast future prices like the head-and-shoulders and double-top price patterns. Also, the researchers find that their model can predict positive autocorrelation with sequential price. The prediction is tested and the results are found statistically and economically significant.

Stephen (2008) examines the profitability of using technical models of moving averages and momentum that add up to 1024 technical trading rules in DM/USD. He finds that all
the trading rules are profitable. The profitability is mainly because of the exploitation of exchange rate trends; the result stay valid even with sub-periods trading and declining profit during late 1980s. The results of the best 25 performing models in-the-sample period from 1973 to 1999 are almost as good as those generated in the out-of-sample period of 2000-2004 in the majority of the cases. It is worth to mention that the risk of making losses when applying each of these models is almost zero, adding another plus to the profitability of technical analysis in trading foreign exchange currencies.

Profitability of technical trading rules is examined in combination with other factors as well. Krishnan and Menon (2009) study the influence of foreign currencies, technical indicators and time frames on trading profits. The research covers the period from September 2006 to October 2008 with 1,400 observations in the sample and two durations: one year and three months. The currency pairs include EUR/USD, GBP/USD, USD/CHF and USD/JPY. The time frames cover five minutes, 15 minutes, 30 minutes, one hour, four hours and one day. The technical indicators used are five leading and five lagging. The findings reveal that using technical analysis in foreign currency trading activities is profitable; all of the currencies, technical indicators and time frames play significant roles in generating profits in foreign exchange spot markets. EUR/USD is found the most profitable and the least risky. The findings also show that short -term trading is riskier and of low liquidity, compared to the long-term trading. Moreover, the authors find that using a combination of technical indicators in a trading system generate remarkable profits.

Researchers keep exploring various trading rules scientifically. Cekirdekci and Iliev (2010) test different set ups as well as exit strategies for trading opening range breakouts of 30 -minute time frame. The research examines a technical trading system using and back tests of around 250 stocks from various industry sectors, from April 2005 to April 2010. The initial tested set ups include buy and sell filters, inside bar, simple and exponential moving averages, a volume indicator, per cent trailing exist, overbought and oversold areas of Relative Strength Index and ATR Ratchet. The
results show that, when combining buy and sell signals with other indicators, such as the volume indicator, the opening range is a powerful model; it generates significant returns when traded with the correct stock.

Similarly, Holmberg, Lönnbark and Lundström (2012) test the profitability of the trading strategy of the "Open Range Breakout (ORB), but in the US crude oil futures prices from March, 1983 to January, 2011. The ORB is a trading rule that signals entry and exit rules once the price moves beyond predefined boundaries. Using the joint distribution of low, high, open and close prices over a period of time, the researchers find that their ORB trading rule significantly generates high returns.

Interestingly, some researchers have conducted different types of studies to have an indication of how widely technical analysis is applied in the financial field. Using a questionnaire survey on behalf of the Bank of England in November 1988, Taylor and Helen (1992) find that around 90 per cent depends on technical analysis in forming their views at different time horizons. The results show that technical analysis is applied mainly for the shorter time frames for entry and exit timings. Moreover, technical analysis tools are found to be the best tools for trading currencies. The survey results also reveal that fundamentals are reliable for the long term picture, whereas others rely on both fundamental and technical analyses in taking trading decisions.

Shifting to the examination of technical analysis in presence of central banks interventions, both early and modern researches show the importance of such interventions when used with trading rules in the foreign exchange markets. Silber (1994) is among the first researchers who examine the profitability of simple trading strategies in foreign exchange markets in presence of central banks' interventions. His sample covers the German mark, Swiss franc, Japanese yen, British pound and Canadian dollar. He uses simple moving averages as trading rules. He finds evidence that technical rules can be valuable in markets where governments are found big players. The results show that government interventions provide speculators with an
opportunity to generate abnormal returns by applying simple technical trading strategies.

There are other researchers who also examine the impact of central bank intervention on the predictability of trading rules in foreign exchange markets. LeBaron (1998) reviews some evidence that shows predictive value over future foreign exchange prices. He analyses the profitability of simple trading rules in relation with central bank activity, using intervention information from the Fed. His forecasts are assessed over one day and one week periods. His sample uses weekly and daily foreign exchange rates of Deusche mark (DM) and Japanese yen (JP) from January 1979 to December 1992. The interest rate series used is one week Euro rates. The trading rules compare the current price with a moving average of historical prices. He finds that the predictability of exchange rates diminishes during the periods when the Fed is inactive. This leads to the conclusion that there is a positive correlation between the Fed intervention in the market and the profitability of the trading rules used to predict foreign exchange rates.

Using a genetic programming for the Duetuche mark, Japanese yen, British pound and Swiss franc, and US official intervention, Neely and Weller (2000) show that interventions could be considered as trading signals themselves. They use simple moving averages as trading rules covering a sample from 1975 through 1998. In fact, they don't support earlier observations that find intervention activities lead to profit in the foreign exchange markets. Their findings rather show that the profitability of technical trading rules is a result of strong and constant trends in exchange rates, which intervention is intended to turn around.

Moreover, analyzing daily exchange rates of USD/DEM as well as daily USD and DEM overnight Euro rates, from January 1979 to July 1994, Saacke (2002) provides further evidence of the unusual profitability of applying technical trading strategies on days when the Fed and Bundesbank interventions take place. The central banks are found to gain returns when they intervene in foreign exchange markets and with the usefulness
of technical analysis. Intervention returns and trading rule profitability are evaluated during horizons and post interventions. Exchange rates are found to react in the opposite direction of central banks' intentions in the short term, but in line with their targets in the long term. The researchers find that the trading rules of using moving averages are considerably profitable on the days when the central banks interfere. The findings also reveal that trading rules returns are still high on days in which interventions did not take place or on preceding days. This means that central banks' interventions are not the only cause of trading rule returns. Shik and Chong (2007) also find out that the technical rules correlate positively with the interventions of the central banks.

There is little attention given to the Japanese candlestick patterns in the literature even though they were widely used in rice trading activities in Japan, and have been found very powerful when combined with other technical trading rules (Nison, 2003). Recent studies on the Japanese candle patterns are found. Goo, Chen and Chang (2007) examine the profitability of Japanese candlestick patterns using daily data. Their sample includes 25 shares that are partially listed in Taiwan Top 50 Tracker Fund and Taiwan Mid-Cap 100 Tracker Fund, for 12 years from 1997 to 2006, and with 2,580 observations for each stock. The main objective of the study is to indentify profitable candle patterns as well as profitable holding periods that would generate abnormal returns for investors. They use six bullish single-line patterns and seven bullish candle pasterns for ten holding periods using a stop-loss strategy as well. The first group includes the long white candle, the white Marubozu, the closing white Marubozu, the opening white Marubozu, the dragon doji and the paper umbrella; the second group includes the hammer, the bullish engulfing, the piercing lines, the bullish harami, the three inside up, the three outside up and the tweezers bottom. The t test is used to statistically test the profitability of the patterns; NOVA and Duncan's various range tests are also applied to compare the profitability of the patterns across the ten holding periods. In general, the results show that there is evidence of some profitable candle patterns at different holding periods. The researchers find that the bullish reversal patterns are the most profitable patterns and that the profitability of various candle
patterns depends on the holding periods. Another finding is that the long holding periods are appropriate for the two candle categories with few exceptions. The results also show that the $-5 \%$ stop-loss strategy does improve the performance of the candlestick trading rules.

Lana, Zhanga and Xiongb (2011) develops a model that visualizes Japanese candlestick patterns in Chinese stock markets. The model transforms the prices of open, close, high and low into "fuzzy" candle charts. The sample includes selected stocks listed in four markets:" SSE A Share, SSE B Share, Shenzhen A share and Shenzhen B share" from January 2000 to December 2010. The results show that the model is able to identify the reversal patterns and that it can be used to indentify early stock reversal signals through "symptoms sequence". The researchers will further enhance the model with additional fuzzy variables to reflect candlestick lines, such as the position of body and shadows to fine-tune the prediction results.

In addition to the previous studies, Haibin, Zhao and Wang (2012) examine the performance of the Japanese candlestick patterns in predicting equity returns using both in-sample and out-of-the-sample forecasts. Monthly data of main global financial markets are used; these markets include "FTSE100, DAX, CAC40 in Europe; NIKKEI225 (NK), HangSeng (HS) and Strait Times (ST) in Asia". Also, monthly data of Standard and Poor's 500 (S\&P500) is collected to find out if the candle patterns have reached the US markets as well. The researchers find that the Japanese candlestick patterns do have predictive power in both in-sample and out-of-sample forecasts. In all the cases, the Japanese trading rules are found superior to the simple buy-and-hold. Also, it is found that there is important information that spreads out from the US stock market to the other financial markets

Lu, Shiu and Liu (2012) investigate the profitability of candle patterns that are composed of two lines through buying on bullish (bearish) patterns and holding the trades till bearish (bullish) patterns take place. Their sample includes daily prices of stocks listed
in the Taiwan Top 50 Tracker Fund from 29 October 2002 to end of 2008. The researchers study three bearish reversal patterns and three bullish reversal patterns. These are the bearish engulfing, the harami, the dark-cloud cover, the piercing lines, the bullish engulfing and the bullish harami, respectively. The bootstrap methodology is used. The results show that the three bullish patterns are found generally more profitable than the beaish patterns. The returns of the three bullish patterns are found statistically significant in the Taiwan stock market.

On the other hand, some researches find conflicting results or even variations within results that are not in line with the findings above. The results vary from lacking of evidence of the profitability to declining profits when simple trading rules are applied. Levich and Thomas (1993) note weak evidence that the profitability of their rules declines in their final subsample period, 1986 to 1990. Lee and Mathur (1996) apply moving averages and channel trading systems on ten currency pairs in foreign exchange spot market. Their sample includes "AUD/JPY, GBP/JPY, CAD/JPY, DEM/GBP, DEM/ITL, DEM/JPY, DEM/CHF, CHF/GBP, and CHF/JPY". They find both trading systems are not profitable.

LeBaron (2002) finds that the abnormal returns resulting from applying a 150-day moving average, from June 1973 to August 2002, decrease during the 1990s. His sample covers the British pound, German mark and Japanese yen. He assumes that data snooping or economic issues could be the main reason for earlier positive results. Applying simple moving average trading rules on longer time periods, Olson (2004) also finds different results on the profitability of the moving average trading rules. He recustomizes moving average rules in a five-year period from 1971 to 1995. He then tests the trading rule in 5-year out-of-sample period. He finds that trading rule returns decline over time after 1970s, to approximately zero by the 1990s. This suggests that the inefficiencies of markets that are reported in earlier studies might have been temporary. Furthermore, Lento and Gradojevic( 2007) find that individual trading rules do not
generate any profits above the buy-and-hold strategy when the technical rules are applied in the DJIA.

Pukthuanthong-Le and Thomas (2008) re-assess the ability of technical trading rules to statistically and economically generate significant returns. Their data covers liquid currency futures from 1975 to 2006. The results show that the profitability of trend following decline for the major currencies of British pound, Japanese yen, German mark /Euro, Canadian dollar, Swiss franc and Australian dollar. Moreover, the researchers find that the related cross exchange rates of the major currencies also decline in the mid of 1990 s.

Poor evidence of profitable candlestick strategies is also found in the literature. Brashears and Elam (1993) explore the profitably of the Japanese candlestick trading and their ability ot forecast reversals in the cotton futures market from 1973 to 1990.Their sample includes 13 candle reversal patterns. The bullish patterns include the hammer, the engulfing pattern, the morning star, the doji star, the piercing lines and the tweezers bottom. The bearish patterns include the bearish engulfing, the upside gap two crows, the hanging man, the dark-cloud cover, the shooting star, the evening star and the tweezers top. These patterns are programmed individually using MetaStock programme. The final results show that no definite evidence of predictive power for the Japanese candle patterns in cotton futures markets. The researchers recommend that additional studies should be conducted to re-examine the predictive power of the Japanese candle trading rules in the future.

Marshall, Young and Rose (2005) study the candle patterns in actively traded stocks listed in the DJIA. The sample includes data from 1992 to 2002; the starting year is selected to make sure that market participants had basic background of the different Japanese candle trading rules and they already started using them at that time in their trading strategies. The sample includes 28 candle patterns that fall under four main categories: bullish single lines, bullish reversal patterns, bearish single lines and bearish
reversal patterns. To test the results, they use the bootstrap methodology to generate random prices of open, high, low and close. Contrary to the researchers' expectations, the final results show no evidence of profitable candle patterns in DJIA, thus, supporting the weak form of the EMH.

Moreover, Young and Marshall (2007) test the predictive power of the Japanese candlesticks in the US stock market, particularly the DJIA Index, from 1992 to 2002. The authors use the $t$ test and the bootstrapping methodology to test the results statistically. The Japanese candle patterns are technical trading rules that have been used in Japan for centuries. The use of these candle patterns has been growing among market participants all over the world because they used to be successful with the rice trading in Japan. The authors use 28 candle patterns that vary from one- to three-candle patterns. These patterns include the long white, the white the Marubozu, the hammer, the bullish harami, the three outside up, the gravestone doji, the shooting star, the darkcloud cover and the tweezers top. The findings show that candle trading rules are statistically not profitable. None of the single and multiple candlestick patterns, bullish or bearish, give timing signals. The authors recommend to use candlestick trading rules in combination with other market timing tools.

The section below summarizes the different findings in the literature above along with comments and criticism.

### 4.3 Summary, Comments and Criticism

From the previous literature, the studies have reported mixed results about the success of technical trading in foreign exchange and stock markets. Abnormal returns are observed in many studies, while other studies report less success of technical trading rules.

Longworth (1981) uses CAD/USD spot and forward rates and finds that forward rates can be predicted using spot rates, concluding that markets are not efficient. Brock, Lakonishok and LeBaron (1992) examine moving averages and range breakouts and find that buy signals constantly produce higher returns than sell signals. Levich and Thomas (1994) find technical trading rules are significantly profitable on contracts of 15year currency futures. Later on, Gencay (1997) also find strong evidence of profitable simple technical trading rules in daily DJIA, supporting the previous results. Osler (2000) finds the technical trading rules of support and resistance levels are powerful predictive indicators. Clustering of foreign currency stop-loss orders and take-profit orders in major foreign currencies are clear indicators of profitable technical trading rules (Osker, 2003). Omrane and Oppens (2004) find evidence of profitable chart patterns that are tested statistically.

More recent studies also provide strong evidence of profitable simple moving average trading rules. Shik and Chong (2007) find the profitable simple moving average rules when moving averages and Relative Strength Index (RSI) are applied on six foreign currencies. Lento and Gradojevic (2007) further enhance technical trading rules through a combined signal approach. The results show that the strategy does outperform the buy-and-hold trading strategy. Park and Scott (2007) re-visit the historical testing measures of the profitability of technical analysis in the empirical literature and find the majority of the studies find technical analysis profitable. Similar to the results found by Omrane and Oppens (2004) in the foreign exchange market, Friesen, Weller and Dunham (2007) provide a modal that shows evidence of how price pattern trading rules can be profitable in the US stock markets.

Moreover, Stephen (2008) finds moving averages and momentum in German Mark profitable. Results of Krishnan and Menon (2009) reveal that all currencies, technical indicators and time frames play significant roles in generating profits in foreign exchange spot markets. Cekirdekci and lliev (2010) find trading opening range breakouts, when combining buy and sell signals and other indicators, a powerful model.

This is in line with the results found by the earlier researchers (Lento and Gradojevic, 2007; Krishnan and Menon, 2009). In very recent studies, Holmberg, Lönnbark and Lundström (2012) find "Open Range Breakout (ORB), in the US crude oil futures prices, significantly generates high returns.

Other studies, both old and modern, examine the central banks' interventions along with trading strategies in the foreign exchange markets. The researchers find that simple trading rules are considerably profitable on the days when the central banks interfere. Silber (1994) is among the first researchers who find evidence that technical rules can be valuable in markets where governments are found big players. LeBaron (1998) reviews some evidence of profitable simple trading rules in presence of the Feb central bank activity. He finds that the predictability of exchange rates diminishes during the periods when the Fed is inactive. This leads to the conclusion that there is a positive correlation between the Fed intervention and the profitability of the technical trading rules. Neely and Weller (2000) show that interventions could be considered as trading signals themselves. Moreover, Saacke (2002) provides further evidence of the unusual profitability of applying technical trading strategies on days when the Fed and Bundesbank interventions take place. Shik and Chong (2007) also find that the technical rules correlate positively with the interventions of the central banks.

Evidence of profitable Japanese candle patterns is also found in the literature. Goo, Chen and Chang (2007) find evidence of some profitable candle patterns at different holding periods with bullish reversal patterns as the most profitable patterns The model developed by Lana, Zhanga and Xiongb (2011) also show that it is able to identify the reversal patterns and that it can be used to indentify early stock reversal signals through "symptoms sequence". Haibin, Zhao and Wang (2012) find in all the cases, the Japanese trading rules are found superior to the simple buy-and-hold. Lu, Shiu and Liu (2012) find evidence of three profitable bullish patterns in the Taiwan stock market.

On the other hand, some researches find conflicting results or even variations within results that are not in line with the findings above. The results vary from lacking evidence of profitable technical trading rules to declining profits when simple trading rules are applied. Levich and Thomas (1993) note weak evidence in their final subsample period, 1986 to 1990. Lee and Mathur (1996) apply moving averages and channel trading systems on ten foreign currencies, and find both trading systems are not profitable. LeBaron (2002) finds that abnormal returns resulting from applying a 150day moving average decrease during the 1990s. Olson (2004) also finds different results on the profitability of the moving average trading rules. He finds that trading rule returns decline over time after 1970s, to approximately zero by the 1990s. Moreover, Lento and Gradojevic( 2007) find that individual trading rules do not generate any profits above the buy-and-hold strategy in the DJIA. In more recent studies, Pukthuanthong-Le and Thomas (2008) find that the profitability of trend following decline in major currencies.

Evidence of profitable Japanese candle patterns is also found poor. Brashears and Elam (1993) find indefinite evidence of predictive power for the Japanese candle patterns in cotton futures markets. Marshall, Young and Rose (2005) find no evidence of profitable candle patterns in DJIA. Similarly, Young and Marshall (2007) find no evidence Japanese candle patterns in the DJIA

Though the majority of the findings in the literature supports the profitability of technical analysis in foreign exchange markets as well as other financial markets, the weak evidence found in some studies need to be examined closely.

In order to support or reject the theory of the Random Walk and Efficient Market Hypothesis, the debate on the mixed results can be objectively made. The weak evidence of profitable trading rules found by some researchers since 1980s (Brashears and Elam, 1993; Levich and Thomas, 1993; Lee and Mathur, 1996; LeBaron, 2002; Olson, 2004; Marshall, Young and Rose, 2005; Lento and Gradojevic, 2007 and Young
and Marshall (2007) is opposed by strong evidence found by others using large samples and targeting different markets in different regions (Longworth, 1981; Brock, Lakonishok and LeBaron, 1992; Gencay, 1997; Osler, 2000; Saacke, 2002; Osker, 2003; Goo, Chen and Chang, 2007; Shik and Chong, 2007; Lento and Gradojevic, 2007; Park and Scott, 2007; Stephen, 2008; Cekirdekci and Iliev, 2010; Lana, Zhanga and Xiongb, 2011; Haibin, Zhao and Wang, 2012; Lönnbark and Lundström, 2012 and Lu, Shiu and Liu, 2012)

Most of the trading rules tested in the literature are very simple, such as moving averages and range breakouts. Moving averages can be easily modeled and tested; however, it is a lagging indicator and generates false signals when used in range trading trends or periods. Also, the poor evidence of profitable candle trading rules could be due to the samples taken for the periods prior 2000 in which the knowledge of these trading rules might not be as solid as during 2000s and onwards. The inconsistency in using statistical tests and the issue of data snooping may lead to conflicts in results. These are some of the factors that could explain the weak evidence in the literature. The strong evidence and the conclusion of inefficient markets in other studies, are challenged by the methodologies and standard statistical analysis used to examine the profitability of technical analysis. The different bubbles and major bullish trends that usually lead to excess price volatility periods and the ignorance of good testing procedures that address data snooping and other issues could be some of the main reasons the findings are positively biased. This is supported by the findings found by Park and Scott (2007). Most empirical researches are subject to various issues in their testing processes, such as data snooping, different selections of trading rules, inand out-of-sample data, search technologies and difficulties in estimating risk and transaction costs.

Furthermore, the impact of central bank activities on the returns is assumed to be reflected in the market price. Technical analysts should not consider them as a major source of the predictive power of some technical trading rules as found by the
researchers above. Intervention activities are similar to other major economic data that affect exchange rates and alert traders to take positions once prices are close to support and resistance levels. However, technical analysis is known for discounting all the known and unknown information.

Regarding the application of trading rules, financial markets are too complex to be predicted by a single trading rule. A trading system that is a combination of different trading rules is found to work better that a single technical tool. It is always recommended to use a combination of good technical indicators as filters in which the majority will agree on clear signals. The findings about the Japanese candlestick patterns are just a simple message that single technical tools fail most of the time. They should rather be used in combination with other powerful technical tools that can best work during the underlying trend.

After consulting the mixed results, it is very important to consider important key factors that would have a high impact on the overall research findings in regard to the profitability of technical trading rules in financial markets. The reasons for the existence of these abnormal returns or weak evidence may not be easy to interpret and justify. However, there are certain obvious factors that play major roles in reaching final results of any study, that need a careful examination and testing. These factors include 1) the possibility of changing trading rules using different time frames in line with the major underlying trend; 2) the consistency of profitable trading rules; 3) the liquidity of the financial markets as it would be more incentive for market participants to trade away inefficiencies; 3) the bullish and the bearish cycles of the markets; 4) the efficiency of trading systems that are made of powerful technical trading indicators, suitable to the underlying market trends; 5) clear understanding of the trading rules of lagging and leading indicators; 6) understating different objectives of major players including activities of central banks' interventions; 7) the usage of sophisticated non-linear models; 8) the usage of good statistical testing procedures, addressing data snooping
and transactions costs and 9) the importance of having good parameters in place that would turn technical analysis into a science.

This research contributes to the literature by testing the predictive power of the Japanese candlestick reversal patterns in the foreign currency market. The findings are compared to all the findings of profitable technical trading rules in general and to the results pertaining to the studies conducted on Japanese candlestick patterns.

## Chapter 5

## Introduction to Technical Trading Rules

## Chapter 5: Introduction to the Technical Trading Rules

The technical trading rules of the Japanese candlesticks are very popular. The Japanese have applied this charting along with its technical rules for centuries. Its popularity arises from its method to display security data for chart analysis and the use of certain candlestick combinations that reflect the psychology of the market participants. The data of the Japanese candlesticks uses the same data of standard bar charts: open, high, low and close. However, the visual effect of the candlestick charts provide a much better picture of the market that is easily displayed, interpreted and analyzed. The price actions look like candles with wicks or shadows. That is the reason why they are called candlesticks. In its simplest form, a white body means that the close is higher than the open, whereas the black body means the close is lower than the high.

There are different shapes for the Japanese candlesticks. They also come in different combinations based on the relationship between open, high, low and close prices. There are various patterns of Japanese candlesticks; a Japanese candlestick pattern may consist of one candlestick or a combination of two or more, but never more than five. Most of the patterns can be used to warn of reversal levels in the markets. These patterns can be bearish, bullish or continuation. Generally, reversal patterns of bullish implications have their inverse patterns which have bearish meaning. The third category includes a few patterns that fall under continuation patterns. Similar to the reversal patterns, continuation patterns have bullish patterns and their opposite bearish patterns in relation to the previous trend that takes place prior to the consolidation phase. Examples of bullish patterns that warn a reversal of the trend from a downtrend to an uptrend includes the piercing lines, the morning star, the bullish Doji Star, the bullish engulfing, the hammer, the bullish harami and the kicking patterns. Examples of bearish patterns that warn a trend reversal from an uptrend to a downtrend includes the darkcloud cover, the evening star, the hanging man, the bearish engulfing, the shooting star, the abandoned baby and the bearish harami. The continuation patterns include the
rising and the falling three methods, the separating lines, the downside gap three methods and the three-line strike (Murphy, 1999). Appendix 1 shows the different Japanese candlestick patterns. Moreover, the Japanese candlestick patterns can be used jointly with other western technical tools, such as oscillators and other technical indicators, which can create a powerful synergy of techniques.

Below is a brief description of each of the eight Japanese candlestick reversal patterns used in the analysis. These patterns follow the descriptions provided by Nison (2001). The description of the candle patterns are followed by an explanation of the common technical indicator of the Relative Strength Index (RSI) that is used along with three candle patterns as a filter.

Four bullish and four bearish candle patterns are used in the analysis of this research. The bullish patterns include the bullish engulfing, the piercing lines, the bullish hammer and the bullish doji star, whereas the bearish patterns include the bearish engulfing, the dark-cloud cover, the hanging man and the shooting star. The following order of the patterns' descriptions is based on the similarity and the inverse relationship of the patterns for easy understanding. A snap shot of each candle pattern that are indentified in the analysis, using excel formulas discussed under methodology, is provided.

The bullish engulfing pattern is a major reversal signal that consists of two real bodies of opposite colours. The market is in a downtrend; then a long white candle closes higher and engulfs the previous black candle. This shows that the bulls have taken over from the bears and that the buying pressure becomes stronger than the selling pressure. The bearish engulfing pattern is just the opposite. The market is in an uptrend; then the last white candle is wrapped by a black long body, signaling a top reversal. This means that the selling pressure has overwhelmed the buying pressure. There are three criteria for the engulfing pattern: 1) the market should be clearly in an uptrend or downtrend, even if it is a short-term trend; 2) there are two candlesticks that form the pattern in which the second body must wrap the previous real body and 3) the colour of the second real
body should be the opposite of the first real body colour (Nison, 2001). Figures (1) and (2) show the two patterns that are identified in USD/INR and EUR/USD pair currencies.


Figure (1): The bullish engulfing pattern in USD/INR


Figure (2): The bearish engulfing pattern in EUR/USD

The piercing lines are a two-day bullish pattern that signals a bottom reversal after a downtrend. The first candlestick is a black body and the second day is a long white body. The second day opens with a downside gap, below the low of the previous day and closes higher and above the mid-point of the first black body. The greater the penetration of the white bodies into the previous black body, the greater the chance for bottom reversal. An ideal pattern requires a second day penetration of more than 50\% of the prior black real body. The psychology behind this pattern is that the market is in a downtrend reflected in the first bearish black body. On the next day, the market opens lower with a gap reflecting more bearish sentiment. Suddenly the bulls take over and manage to close the market not only at previous close but higher into the previous body mid-point or even slightly higher. The bears will have their second thoughts about their short positions. The longs will see that the new lows could not hold and probably it is time to go for long positions. There are four main factors that indentify the importance of the piercing lines: 1) the degree of the second day penetration within the first black body, the greater the penetration degree, the greater the likelihood for a bottom reversal; 2) the second day opens below a main support level but fails and closes higher, with bears being unable to control the market and 3) heavy volume on the opening of the second day, an initial selling off is followed by buying blow offs (Nison, 2001). Figure (3) represents the piercing lines pattern that is identified in AUD/USD pair currency.


Figure (3): The piercing Lines pattern in AUD/USD

The dark-cloud cover is the opposite formation of the piercing lines pattern. It is a twoday bearish pattern that signals a top reversal after an uptrend. The first day is a long white real body. The second day opens above the high of the previous day but closes near the low of the day within the previous day white body. The greater degree of penetration into the previous day body, the more likely a top reversal will take place. Some technical analysts require more than $50 \%$ penetration of the second day close to the previous white real body. The psychology behind this pattern is that the bulls are in full control when the second day open with an upside gap; however, the bulls lose control and no continuation of the rally takes place. Then the market closes near the close and the bulls will have a second thought about their long positions. Similar to the piercing lines pattern, there are important factors that intensify the significance of the dark-cloud cover pattern, but in the opposite direction (Nison, 2001). Figure (4) represents the pattern that is identified in EUR/USD pair currency.


Figure (4): The Dark-cover cloud in EUR/USD

The hammer is the third bullish candlestick pattern; it is a one-day pattern. The body of the hammer can be white or black, but it is more bullish if the body is white because it closes at the high. The hammer has a long lower shadow and closes near the high of the session. The psychology behind this pattern is that the market sells off sharply during the session but then bounces back at the close near to the small body's high. The hammer may have no upper shadow or a very small one enforcing bullish implications. This clearly shows that the bears have lost control and they are now having second thoughts. The main characteristic of the bullish hammer is that the lower shadow should be at least twice or three times the height of the body (Nison, 2001). Figure (5) represents the bullish hammer pattern that is identified in GBP/USD pair currency.


Figure (5): The bullish hammer pattern in GBP/USD with the RSI filter

The hanging man looks like a hammer; however, it forms after an uptrend rather than a decline. Since the long lower shadow has a bullish implication, it is best to wait for a bearish confirmation with this pattern. A lower opening below the body of the hanging man on the second day and a lower close will be a good confirmation of a top reversal. The psychology behind this is that when the market closes on the next day below the body of the hanging man, the bulls who bought on the open or close of the hanging man day will be left hanging with a bad position, and are now more nervous for potential big losses. Thus, they may decide to cut their losses and liquidate, adding more selling pressure. The key factors for a reversal hanging man pattern are a preceding uptrend and a next day close below the hanging man close (Nison, 2001). Figure (6) represents the pattern that is identified in USD/JPY pair currency.


Figure (6): The hanging man pattern in USD/JPY with the RSI filter

The fourth and the last bearish candle pattern used in the sample analysis is the shooting star. It is a one-day pattern with a small real body and a long upper shadow. The small body can be white or black. This pattern looks like a shooting star with its tail glowing in the sky. An ideal shooting star day opens with an upside gap, but this gap is not always important. This pattern indicates that the market is rejecting a higher high. A close on the next day below the shooting star close can give a good confirmation of potential top reversal (Nison, 2001). Figure (7) represents the pattern that is identified in USD/CAD pair currency.


Figure (7): The shooting star pattern in USD/CAD with RSI filter

The fourth and the last bullish pattern in the analysis is the doji star. A star is usually a small real body, white or black, that gaps away from the prior real body. If the star is a doji rather than a small real body, it is named a doji star or a doji line that warns a near reversal. Doji candlesticks can have shadows of different lengths. The doji candlestick used in the analysis is a one-day pattern in which the open price and the close price are equal. The star or doji star can be part of other reversal patterns, such as the morning star, the evening and the harami. Doji candlesticks can have shadows of different lengths. Generally, the doji lines show indecision between the market participants. The likelihood of a reversal with a formation of a doji increases if 1) the following candlesticks confirm a potential reversal; 2) the market is in overbought or oversold situations and 3) the market doesn't form doji so often (Nison, 2001). There are different versions of doji candlesticks, such as long legged doji, gravestone doji and dragonfly doji. The doji that is used in the analysis has equal open and close prices regardless the shadows length, and signal for bottom reversal (Nison, 2001). Figure (8) represents the doji star pattern that is identified in USD/ZAR pair currency.


Figure (8): The doji star pattern in USD/ZAR

In addition to price patterns, resistance-support levels and Japanese candlestick patterns, technical analysts use a lot of technical indicators that be used in trending markets, non-trending markets and gauging sentiments. There are technical indicators or oscillators used in the non-trending markets that can still be used in trending markets to get further insights into the market momentum. Among these indicators is the Relative Strength Index (RSI). The RSI and the other oscillators, when used in combination with price charts and Japanese candle patterns, become extremely valuable. They provide traders and technical analysts further insight especially into the short-term market extremes that are known as overbought or oversold conditions.

The Relative Strength Index ( RSI ) is considered one of the most popular technical indicators used actively by traders. It basically measures the internal strength of a security. It focuses on price momentum, specifically the changes in closing prices. It ranges between zero and a hundred. It usually tops and bottoms above and below 70 and 30 readings, respectively. These are overbought and oversold conditions (Colby, 2003). A crossing above 30 indicates a buying signal, whereas a crossing below 70
indicates a selling signal. Divergences between the price action and the indicator movements also provide warning signals of potential bottom and top reversals. In addition to the signals of the oversold-overbought condition, the crosses signals of the midpoint are also used by many traders. Since oscillators are best used in non-trending markets and there is a risk of misusing the indicator, the 50 reading is used as a midpoint value to divide the horizontal range into two halves. The 50 midpoint is also used as buy and sell signals. The time span used is 14 days by default and it will be used in the analysis. The RSI formula is also introduced later in the methodology section. Figures (5-7) show the three patterns that are identified using the excel formula and the RSI filter.

## Chapter 6

## Methodology

## Chapter 6: Methodology

This research attempts to re-examine the weak form of the EMH through the application of Japanese candlestick price patterns, as technical trading rules, in foreign exchange markets. It tests two null hypotheses that assume 1) all the Japanese candlestick reversal patterns cannot be used to predict returns in foreign exchange markets, and that 2) foreign exchange markets are efficient. The two alternative hypotheses state that 1) Japanese candlestick reversal patterns can be used to predict market movements, and that 2) foreign exchange markets are inefficient. The one-tailed $z$ score test is used to test the hypotheses at $5 \%$ level of significance. The following sections include the sample data and the analytical tools used in the analysis, followed by a discussion of data analysis and a summary of findings and recommendations.

### 6.1 Sample Data

The sample data includes seven foreign currencies from both advanced and emerging financial markets. These currencies include the Australian dollar (AUD/USD), British pound (GBP/USD), Canadian dollar (USD/CAD), Euro dollar (EUR/USD), Japanese yen (USD/JPY), Indian rupee (USD/INR) and South African rand (ZAR). The sample covers a 12-year span, which is from $1^{\text {st }}$ January 2001 to $31^{\text {st }}$ December 2012. These currencies reflect good financial environment to test the technical trading rules of the Japanese candlestick patterns in which most of market participants and academicians are interested in. All the data analysis uses daily OHLC bid rates: open (O), high (H), low (L) and close (C), obtained from the financial data provider, Thomas Reuters. The total observations in the sample are 3,129 .

### 6.2 Analytical Tools

This section explains the technical trading and statistical tools used in the analysis to test the proposed null hypotheses. It discusses the Japanese candle patterns used, challenges faced, filters applied, holding periods to calculate returns (losses), followed by statistical tests to help deciding whether to reject or accept the null hypothesis.

There are eight Japanese candlestick reversal patterns used in the analysis: four bullish patterns and four bearish patterns. The eight candle patterns are tested for each of the seven foreign currencies.

The bullish patterns include the hammer, the piercing lines, the doji star and the bullish engulfing, whereas the bearish patterns include the hanging man, the dark-cloud cover, the shooting star and bearish engulfing. The reason of selecting these patterns is that they are very popular and most of them are considered major reversal patterns. Another reason is the ability to transform these candlestick patterns and practice them in a scientific manner through using excel formulas that can describe and indentify the patterns, and enable back testing.

The main challenge encountered in this research is the application a scientific method that would address the subjectivity of using the Japanese candlestick patterns as technical trading rules. Moving technical analysis to a science through transforming subjective candle patterns into objectively defined testable patterns has always been a challenge. There are not so many mathematical definitions of the Japanese candlesticks in the literature. Some of the excel formulas that are used in the analysis are obtained from other resources. These formulas are further amended to address the subjectivity of different variations of the candle patterns used in the analysis, which are in line with Nison's (2001). The excel formulas (3), (4) and (7), mentioned later in this section, are obtained from a paper written by Fadhel (2010) with an amendment made to formula (7) to differentiate the shooting star pattern that shows at tops from the
inverted hammer pattern that shows at bottoms; an additional condition of a next day lower close is added. This is in line with Nison's (2001). Formulas (5) and (6) are obtained from Tech Excel Charts and Programming Blog posted by BxCapricorn (2009); an additional condition of a lower close and a higher close on the next day is also added to differentiate the hanging man pattern and the hammer, respectively, from other similar patterns that show in opposite directions. These are also in line with Nison's (2001).

Formulas (1) to (8) describe the eight Japanese candlestick patterns: the bullish engulfing, the bearish engulfing, the piecing lines, the dark-cloud cover, the hammer, the hanging man, the shooting star and the bullish doji, against (1), (2), (3), (4), (5), (6), (7) and (8), respectively. Using IF and AND excel functions, the following formulas represent four columns: Column A represents Date, Column B represents Open, Column C represents High, Column D represents Low and Column E represents Close. The formulas start on line or row 5 that represents today; line 4 represents yesterday, line 3 represents the day before yesterday and line 6 represents tomorrow. Number one refers to the patterns identified by the formulas.

$$
\begin{equation*}
=\mathrm{IF}(\mathrm{AND}((\mathrm{~B} 4>\mathrm{E} 4),(\mathrm{E} 5>\mathrm{B} 5),(\mathrm{E} 5>\mathrm{B} 4),(\mathrm{E} 4>\mathrm{B} 5),((\mathrm{E} 5-\mathrm{B} 5)>(\mathrm{B} 4-\mathrm{E} 4)),(\mathrm{C} 5>\mathrm{C} 4), \tag{1}
\end{equation*}
$$ (D5<D4)),1,"")

$=\operatorname{IF}(\mathrm{AND}((\mathrm{E} 4>B 4),(\mathrm{B} 5>E 5),((\mathrm{B} 5-\mathrm{E} 5)>(\mathrm{E} 4-\mathrm{B} 4)),(\mathrm{E} 4<\mathrm{B} 5),(\mathrm{B} 4>\mathrm{E} 5)), 1$, "")
$=\operatorname{IF}(\mathrm{AND}((\mathrm{E} 4<\mathrm{B} 4),(((\mathrm{E} 4+\mathrm{B} 4) / 2)<=\mathrm{E} 5),(\mathrm{B} 5<\mathrm{E} 5),(\mathrm{B} 5<\mathrm{E} 5),(\mathrm{E} 5<\mathrm{B} 4),(\mathrm{B} 5<\mathrm{D} 4)$, $((E 5-B 5) /(0.001+(C 5-D 5))>0.6)), 1, " ")$ E5<=(0.5*(C4+D4))), 1,"")
$=\operatorname{IF}\left(\right.$ AND $\left((\mathrm{C} 4-\mathrm{D} 4)>\left(3^{*}(\mathrm{~B} 4-\mathrm{E} 4)\right),((\mathrm{E} 4-\mathrm{D} 4) /(0.001+\mathrm{C} 4-\mathrm{D} 4)>0.6)\right.$,

$$
\begin{align*}
& \left.((\mathrm{B} 4-\mathrm{D} 4) /(0.001+\mathrm{C} 4-\mathrm{D} 4)>0.6),(\mathrm{E} 5>\mathrm{E} 4)), 1,{ }^{\prime \prime} "\right) \\
& =\mathrm{IF}\left(\mathrm { AND } \left((\mathrm{C} 4-\mathrm{D} 4)>=\left(2^{*}(\mathrm{ABS}(\mathrm{~B} 4-\mathrm{E} 4))\right),((\mathrm{E} 4-\mathrm{D} 4) /(0.001+\mathrm{C} 4-\mathrm{D} 4)>=0.75),\right.\right.  \tag{6}\\
& ((\mathrm{B} 4-\mathrm{D} 4) /(0.001+\mathrm{C} 4-\mathrm{D} 4)>=0.075),(\mathrm{E} 5<\mathrm{E} 4)), 1, " \mathrm{l}) \\
& =\mathrm{IF}\left(\mathrm { AND } \left(\mathrm{~B} 4<\mathrm{D} 4+\left(0.5^{*}(\mathrm{C} 4-\mathrm{D} 4)\right), \mathrm{E} 4<\left(\mathrm{D} 4+0.5^{*}(\mathrm{C} 4-\mathrm{D} 4)\right), \mathrm{OR}\left(\mathrm{~B} 4<\mathrm{D} 4+0.9^{*}\right.\right.\right.  \tag{7}\\
& \left.\left.\left.(\mathrm{C} 4-\mathrm{D} 4), \mathrm{E} 4<\mathrm{D} 4+0.9^{*}(\mathrm{C} 4-\mathrm{D} 4)\right),(\mathrm{E} 5<\mathrm{E} 4)\right), 1,{ }^{*} "\right) \\
& =\mathrm{IF}(\mathrm{~B} 4=\mathrm{E} 4,1 \tag{8}
\end{align*}
$$

Furthermore, the 14-day Relative Strength Index (RSI) is used to distinguish the three similar patterns that appear at different turning points; these similar patterns include the bullish hammer, the hanging man and the shooting star. In addition to the signals of the oversold-overbought condition, the crosses of the midpoint signals are also used by many traders. Since oscillators are best used in non-trending markets and there is a risk of misusing the indicator, the 50 reading is used as a midpoint value to divide the horizontal range into two halves. The 50 midpoint is used as buy and sell signals. For example, crossing 50 to the upside is considered a buying signal, whereas crossing 50 to the downside is considered a selling signal. The 50 midpoint crosses concept is used with the three candle patterns as a filter to distinguish them. If the hanging man and the shooting start patterns form above 50 , it is assumed that there is a high possibility that the trend will reverse from up to down. Similarly, if the bullish hammer pattern forms below the 50 reading, there is a high possibility that the current trend will reverse from down to up. In other words, a reading above 50 indicates potential for a bearish reversal, and a reading below 50 indicates potential for a bullish reversal.

Having used the RSI filter for the three candle patterns, the results are considered only if the average returns are statistically significant at $5 \%$ level for at least five consecutive holding periods. Formula (9) shows how the RSI is calculated as provided by Cably (2003).

$$
\begin{equation*}
\mathrm{RSI}=100-\frac{(100)}{(1+R S)} \tag{9}
\end{equation*}
$$

Where:
$R S=$ the ratio of the exponentially smoothed moving average for $n$-period gains, divided by the absolute value of the exponentially smoothed moving average for $n$-period losses.

After identifying the eight bullish and bearish candle patterns and filtering them through using the RSI overbought and oversold conditions, the returns are computed for seven holding periods: one day, two days, three days, four days, five days, seven days and ten days. For the bullish patterns, the returns represent the difference between the open price, following the pattern day, and close price of the seven holding periods as in formula (10). For the bearish patterns, the returns represent the difference between the open price, following the pattern day, and close price of the seven holding periods as in formula (11). The returns for the holding periods that fall beyond the 31 December 2012 are excluded.

$$
\begin{equation*}
\mathrm{R}_{i}=\left(\underset{t}{\mathrm{C}} \underset{t+2^{\prime}}{\mathrm{C}} \underset{t+3^{\prime}}{\mathrm{C}} \underset{t+4^{\prime}}{\mathrm{C}},{ }_{t+5^{\prime}}^{\mathrm{C}_{t+7^{\prime}}^{\mathrm{C}}} \underset{t+10}{\mathrm{C}}\right)-\mathrm{O}_{t} \tag{10}
\end{equation*}
$$

Where
$\mathrm{R} i=$ the return of the seven holding periods
$\mathrm{C} t=$ day 1 close, following the pattern day
$\mathrm{C} t+1=$ day 2 close
$\mathrm{Ct}+2=$ day 3 close
$\mathrm{Ct}+3=$ day 4 close
$\mathrm{Ct}+4=$ day 5 close
$\mathrm{C} t+6=$ day 7 close
$\mathrm{Ct}+9=$ day 10 close
$\mathrm{O} t=$ day 1 open

$$
\begin{equation*}
\mathrm{R}_{i}=\mathrm{O}_{t}-\left(\underset{t}{\mathrm{C}}, \underset{t+2^{\prime}}{\mathrm{C}}, \underset{t+3^{\prime}}{\mathrm{C}} \underset{t+4^{\prime}}{\mathrm{C}}, \underset{t+5^{\prime}}{\mathrm{C}}, \underset{t+7^{\prime}}{\mathrm{C}} \underset{t+10}{\mathrm{C}}\right) \tag{11}
\end{equation*}
$$

Where
$R i=$ the return of the seven holding periods
Ot = day 1 open, following the pattern day
$\mathrm{C} t=$ day 1 close
Ct+1 = day 2 close
Ct+2 = day 3 close
Ct+3 = day 4 close
Ct+4 = day 5 close
Ct+6 = day 7 close
$\mathrm{Ct}+9=$ day 10 close

Having identified the patterns and computed the returns for the seven holding periods, and following the methodology used by Ramond and Leuthold (1982) and Anderson (2003), the one-tailed z score test is used for each holding period of the pattern. The two null hypotheses are tested at $5 \%$ level of significance that is $95 \%$ confidence level. Also, the same methodology including the holding periods follows Fadhel's (2010), supervised by Anderson (2010), the same author above. Formula (12) represents the $z$ score statistical test that accounts for the gross profit variance from each trade as well as the number of total trades. It allows a comparison of results from various trading rules and time periods. To arrive to the final results using the $z$ score test, the number of times the candle pattern is identified $(n)$ in the formula below, has to be above 30. This formula that considers all the factors above does also provide a method to assess the weak form efficiency of the price series used in the sample analysis. (Peterson and Leuthold, 1982)

$$
\begin{equation*}
z=\frac{\mathrm{X}-X_{0}}{\sqrt{\frac{S^{2}}{\mathrm{n}}}} \tag{12}
\end{equation*}
$$

Where:
X = actual Mean Gross Profits (MGP) from a given strategy

Xo = expected MGP (zero in this case)
S2 = variance of Gross Profits per trade
$n=$ number of trades; it should be above 30

Unlike securities trading, the foreign exchange trading has no guaranteed return or dividend payment. Therefore, the equilibrium expected return is considered zero. Trading foreign exchange currencies is similar to trading futures contracts; it is a twoparty zero sum game, where a price change causes one party to profit and the other party to lose. Thus, since foreign exchange trading is a zero-sum game, zero is considered the rational benchmark as expected mean gross profits. Moreover, the selection for gross profits instead of the net is due to the absence of a standard transaction cost as commissions differ significantly depending on time as well as trader and firm types. Readers can deduct suitable commission charges to have some value for mean net returns. These adjustments should not impact the variance of profits. (Peterson and Leuthold, 1982)

The p -value is calculated to also help decide whether the pattern identified is due to chance or its probability of being formed by chance is really too small. To calculate the $p$-value using the $z$ test statistic, excel formula (13) is used. If the value is equal or below the significance level of 0.05 , this means that the probability of the pattern was formed by chance is very small, at $95 \%$ level of confidence and the null hypothesis will be rejected. However, if the $p$-value is above the 0.05 significance level, it means that the probability the pattern was created by chance is high and the null hypothesis will be accepted.
P-value = 1-NORMSDIST(ABS(z))

Where
ABS = the absolute value of $z$
NORMSDIST = standard normal distribution of $z$

Figures (9-12) show the number of times the four bullish and the four bearish candle patterns appear in the final results. Figures (10) and (12) show the number of times the bullish hammer, the bearish hanging man and shooting star patterns appear after using the RSI filter.


Figure (9): A comparison of the number of times the four bullish candle patterns appear in the seven foreign currencies


Figure (10): A comparison of the number of times the four bullish candle patterns appear in the seven foreign currencies after using the RSI filter


Figure (11): A comparison of the number of times the four bearish candle patterns appear in the seven foreign currencies


Figure (12): A comparison of the number of times the four bearish candle patterns in the seven foreign currencies after using the RSI filter

## Chapter 7

## Discussion of Study <br> Analysis

## Chapter 7: Discussion of Study Analysis

Having tested the profitability of selected Japanese candlestick reversal patterns in foreign exchange markets; this chapter discusses in details the results of analyzing candle reversal patterns in seven foreign currencies for 12-year data of 3,129 observations. The following seven sections discuss the results for each currency pair.

After examining the bullish patterns in AUD/USD currency pair, it is found that the bullish hammer pattern is identified 77 times at less than $5 \%$ level of significance for all the holding periods. When the results are filtered using the RSI, the pattern is identified 40 times in which all are significant at $5 \%$ level except of the seven-day holding period. The bullish doji star is identified 28 times throughout the sample at $5 \%$ significance level. The bullish engulfing pattern is found less profitable, which is not statistically significant either. The piercing lines pattern appears very rare as it shows only 7 times. Similar to the bullish engulfing result, the average returns of this pattern are found statistically insignificant. Shifting to the bearish patterns, the hanging man performs best compared with the other three patterns. The pattern is indentified 89 times in which the average returns are significant at $5 \%$ level of significance. When filtered by the RSI that is more than 50 , the pattern appears 57 times with average returns that are statistically significant. Although the shooting star pattern is identified 148 times, the average returns are found statistically insignificant. However, when filtered for the RSI, the average returns are found statistically significant for the one-day, two-day, three-day and seven-day holding periods. The bearish engulfing and the dark-cloud cover are identified 70 times and four times, respectively and their average returns are found insignificant. Appendix 2 includes the descriptive statistics of the eight candle pattern analysis for AUD/USD.

The analysis of USD/CAD shows poor evidence of profitable bullish candle patterns. The bullish hammer appears 58 times with significant average returns at $5 \%$ level;
however, when filtered using the RSI, the pattern appears only 25 times and the average returns are found significant only for the one-day and three-day holding periods. The bullish engulfing pattern appears 35 times throughout the sample with significant average returns only for the one-day and two-day holding periods. The bullish doji star pattern appears 19 times and is found statistically insignificant. The piercing lines pattern appears only eight times and the average returns are found significant only for the one-day, two-day and ten-day holding periods at $0.00 \%, 0.03 \%$ and $0.04 \%$ level of significance, respectively. This result will not be considered because the number of times the patterns appears, which should be considered in z score formula, is less than 30 . On the other hand, the bearish hanging man and the shooting star patterns show strong evidence of profitability at $5 \%$ level of significance even after being filtered with the RSI. The hanging man pattern is identified 79 times; the shooting star pattern is identified 240 times. After being filtered with the RSI reading that is above 50, the hanging man and the shooting star patterns appear 44 times and 108 times, respectively. The dark-cloud cover is identified only twice with statistically insignificant average returns. The bullish engulfing pattern is identified 35 times and the average returns are considered significant only for the one-day and two-day holding periods. Appendix 3 includes the descriptive statistics of the eight candle pattern analysis for USD/CAD.

In EUR/USD, only the bullish pattern of the hanging man shows average returns that are statistically and consistently significant at $5 \%$ level of significance. This result also repeats when filtered with the RSI. The pattern is identified 64 times and when filtered, it shows 34 times. The presence of the piercing lines pattern is very poor; even though the average returns of the two-day holding period is statistically significant, $0.00 \%$, the pattern is identified only 7 times out of 3129 observations. This result is also not considered. The average returns of the bullish doji star and the bullish engulfing patterns are statistically insignificant. They show 15 times and 49 times, respectively. On the other hand, the average returns of the handing man and the shooting star patterns are statistically significant; they are identified 106 times and 181 times,
respectively. Nevertheless, when filtered for the RSI reading, the average return of the ten-day holding period of the hanging man is found $0.07 \%$ that is statistically insignificant at $5 \%$ level. Also, the average returns of the three-day, four-day and fiveday holding periods for the shooting star pattern are found insignificant: $0.08 \%, 0.09 \%$ and $0.08 \%$, respectively. The dark-cloud and the bearish engulfing patterns are found very poor. Although the bearish engulfing pattern appears 156 times, the average returns are found statistically insignificant. The dark-cloud cover pattern is identified only seven times. Appendix 4 includes the descriptive statistics of the eight candle pattern analysis for EUR/USD.

In GBP/USD, only the average returns of the bullish hammer pattern are found statistically and consistently significant at $5 \%$ level even after filtering for the RSI. The pattern is identified 97 times before applying the RSI filter and 37 times after using the filter. The other three bullish patterns are found statistically insignificant. The piercing lines, the bullish doji star and the bullish engulfing patterns appear 7 times, 17 times and 48 times, respectively. On the other hand, the average returns of the hanging man and the shooting star patterns are found statistically significant at $5 \%$ level. They show 99 times and 197 times, respectively; however, when filtered for the RSI, the average returns of the hanging man pattern are found statistically insignificant for the seven-day and the ten-day holding periods, $0.09 \%$ and 0.26 , respectively. The existence of the dark-cloud cover pattern is found very poor as it is identified only once. The bearish engulfing pattern is identified 131 times and its average returns are also found insignificant. Appendix 5 includes the descriptive statistics of the eight candle pattern analysis for GBP/USD.

In the first emerging foreign currency of USD/INR, the average returns of the bullish hammer and the bullish engulfing patterns are found statistically significant at $5 \%$ level. The patterns are identified 40 times and 65 times, respectively. However, when filtering the bullish hammer using the RSI reading, the average returns are found significant only for the one-day and the ten-day holding periods, $0.00 \%$ and $0.03 \%$, respectively. The
piercing lines pattern appears 33 times but its average returns are found statistically insignificant. The bullish doji star pattern appears 133 times and only the three-day average returns are found significant, 0.02\%, lacking consistency in results. On the other hand, the existence of the bearish patterns in USD/INR is found very poor. The average returns of the hanging man pattern are found statistically significant for only the four-day, five-day and ten-day holding periods; and when filtered by the RSI, only the average returns of the one-day and two-day holding periods are found significant. The pattern is identified 69 times before the RSI filter and 39 times after applying the filter. The average returns of the shooting star and the bearish engulfing patterns are found insignificant. The shooting star pattern shows 549 times before the RSI filter and 244 times after using the filter; the bearish engulfing pattern is identified 55 times. Even though the average returns of the dark-cloud cover pattern are found significant for all the holding periods except the one-day period, this result should not be considered as the pattern is identified only twice. Finally, the bearish engulfing pattern is identified 131 times and its average returns are also found insignificant. Appendix 6 includes the descriptive statistics of the eight candle pattern analysis for USD/INR.

The USD/JPY currency pair lacks evidence of most of the bullish candle reversal patterns. Only the average returns of the bullish hammer pattern are found statistically significant for the first five holding periods, and the first four holding periods after allowing for the RSI filter. The pattern is identified 120 times before the RSI filter and 62 times after applying the filter. The average returns of the bullish doji star and the bullish engulfing patterns are found insignificant for all the seven holding periods; they are identified 25 times and 45 times, respectively. Similar to the previous results, the average returns of the piercing lines pattern are found insignificant except for the twoday holding period, $0.01 \%$. This result is not considered either as the pattern is identified only four times. Moving to the bearish candle reversal patterns, the average returns of both the hanging man and the shooting star patterns are found statistically and consistently significant at $5 \%$ level even after allowing for the RSI filter. The hanging man appears 155 times before the filter and 82 times after the filter; the
shooting star pattern appears 190 times before the filter and 75 times after the filter. The average returns of the dark-cloud cover are found insignificant; the pattern is identified only 4 times. The average returns of the bullish engulfing pattern are found statistically significant only for the four-day holding period, lacking consistency in the overall result. Appendix 7 includes the descriptive statistics of the eight candle pattern analysis for USD/JPY.

Having examined the second emerging market foreign currency and the last foreign currency in the sample, USD/ZAR is found to experience no bullish reversal candlestick patterns. None of the average returns of the four candle patterns are found statistically significant at $5 \%$ level. The bullish hammer pattern is identified 85 times before the RSI filter and 41 times after the filter; the bullish doji star and the bullish engulfing patterns appear 17 times and 26 times, respectively. The piecing lines pattern does not appear at all. However, there is some evidence of bearish candle patterns in USD/ZAR. The average returns of the shooting star pattern are found consistently and statistically significant at $5 \%$ level for all the holding periods before and after the RSI filter. The pattern appears 282 times before the filter and 129 times after the filter. The average returns of the hanging man pattern are found statistically significant for the first five holding periods before and after the filter. The average returns of the dark-cloud cover pattern are found significant only for the three-day and four-day holding periods; the pattern appears only twice. Thus, due to the low frequency of pattern and the lack of consistency, the pattern results are not considered. Appendix 8 includes the descriptive statistics of the eight candle pattern analysis for USD/ZAR.

## Chapter 8

## Findings and

## Recommendations

## Chapter 8: Findings and Recommendations

After analyzing the results in detail, this chapter summarizes the major results into two areas: 1) general findings in term of frequency of pattern appearance, holding periods, significance levels and bullish and bearish trends; and 2) specific findings that are pertaining to each currency pair. The consistency of statistical significant returns at 5\% level for all the holding periods is considered. However, for the three patterns of the shooting star, the hanging man and the bullish hammer, both pre- and post-RSI filter results are considered statistically significant based on one conservative condition; the average returns should be statistically significant at 5\% level for at least five consecutive holding periods in a row in both data; before and after the RSI filter that is above 50 reading for the bearish two candle patterns, and below 50 reading for the bullish candle pattern. Another condition that needs to be satisfied when considering the findings is the number of observations along with the $5 \%$ level of significance. According to Peterson and Leuthold (1982), the number of times the candle pattern is identified should be above 30 in the $z$ score statistic.

Having had more $65 \%$ bullish data during the study sample, and among the four bullish candlestick reversal patterns, the bullish hammer pattern is found the strongest one in term of frequency and statistical significant average returns at $5 \%$ level. The maximum number of times the pattern appears is 97. AUD/USD can be traded using this pattern for the first six holding periods; EUR/USD and GBP/USD can be traded for all the seven holding periods; USD/JPY can be traded for the first five holding periods. The bullish engulfing pattern is found statistically significant only in USD/INR. The research also finds that there is no evidence of the piercing lines and bullish engulfing patterns across all the seven currencies. Two other interesting findings are the very low frequency of the piercing line pattern across the sample; the number varies from four to eight except for USD/INR and USD/ZAR; they appear 33 times and zero times, respectively. Another finding is that both of the emerging market currencies, USD/INR and USD/ZAR, show
poor evidence of bullish candle patterns even though most of the study sample falls under bullish cycles; only the average returns of the bullish engulfing pattern in USD/INR is found statistical significant. These findings reject both of the null hypotheses that assume all Japanese candlestick patterns cannot be used to forecast foreign currency prices, and that foreign markets are efficient. Furthermore, the findings of the profitable Japanese candle patterns are in line with the results found by Goo, Chen and Chang (2007); Lana, Zhanga and Xiongb (2011); Haibin, Zhao and Wang (2012); Lu, Shiu and Liu (2012) on the studies that examine the profitability of the Japanese candle patterns as technical trading rules in particular. These results also support the evidence found using other profitable technical trading rules in general by Longworth, 1981; Brock, Lakonishok and LeBaron, 1992; Gencay, 1997;Osler, 2000; Saacke, 2002; Osker, 2003, 2006; Shik and Chong, 2007; Lento and Gradojevic, 2007; Park and Scott, 2007; Stephen, 2008; Cekirdekci and Iliev, 2010 and Lönnbark and Lundström, 2012.

Moving to the general findings of the bearish candle reversal patterns, strong evidence of the hanging man and the shooting star patterns are found in most of the foreign currencies, which is statistically significant at $5 \%$ level. The highest number of the times the hanging man and shooting star patterns appear is 155 times and 129 times, respectively. The pattern of the hanging man that appears in AUD/USD, USD/CAD and USD/JPY can be traded for all the holding periods, whereas the same pattern can be traded in EUR/USD, GBP/USD and USD/ZAR for the first six holding periods of EUR/USD, the first five holding periods of GBP/USD and USD/ZAR, respectively. The shooting star pattern can be traded in USD/CAD, GBP/EUR, USD/ZAR and USD/JPY for all the holding periods. The research also finds that the number of times the darkcloud cover pattern appears is very low; it is between one and seven in which the average returns are found statistically insignificant. Similarly, the average returns of the bearish engulfing pattern are found statistically insignificant even though there is a high frequency of the pattern that goes up to 181 times. The last interesting finding is that both of the emerging market currencies show evidence of the hanging man and the
shooting star patterns with an average return that is statistically and consistently significant at $5 \%$ level. These findings also reject the two null hypotheses. Moreover, these partial findings that find no evidence of profitability of the other candle patterns, are in line with the other results in the literature that find no evidence of profitable candlestick patterns, particularly in the studies done by Brashears and Elam (1993); Marshall, Young and Rose (2005) and Young and Marshall (2007). As unprofitable technical trading rules in general, the poor evidence of the candle patterns are also in line with the other results found by Levich and Thomas (1993); Lee and Mathur (1996); LeBaron (2002); Olson (2004) and Lento and Gradojevic (2007).

Currency-wise findings are the second part of the research main findings. The bullish hammer can be traded for the first six holding periods as well as the bearish hanging man for all the holding periods in AUD/USD. Traders can trade the bearish hanging man and the shooting star patterns in USD/CAD for all the holding periods. The bullish hammer pattern, the bearish hanging man pattern can be traded in EUR/USD for the first six holding periods. GBP/USD can be traded using the bullish hammer, the bearish hanging man and the shooting star patterns for all the holding periods, the first five holding periods and all the holding periods, respectively. USD/INR can be traded using the bullish engulfing pattern. USD/ZAR can be traded using the bearish hanging man and the shooting start patterns for the first five holding periods and all the holding periods, respectively. Finally, USD/JPY can be traded using the bullish hammer pattern for the first five holding periods; it can also be traded using the bearish patterns of the hanging man and the shooting star for all the holding periods.

After finding strong evidence of some profitable Japanese candle reversal patterns in foreign exchange markets, this research provides recommendations that are divided into two main areas. The first one is in reference to trading and investment decisions. The other area is concerned with future research. Based on the findings above, it is recommended to trade the Japanese candlestick patterns that are found statistically significant at $5 \%$ level in the respective currencies. This is summarized in the second
section above that is pertaining to respective currency pairs. For future research, it is recommended to use more sophisticated algorithm programmes and statistical models to re-examine the findings of this research not only using daily prices but also intraday timeframes. Since foreign exchange markets are known for being very complex and difficult to predict, it is recommended to use other technical trading rules, such as support-resistance levels and oscillators like the MACD histogram and Commodity Channel Index (CCI) in combination with the candlestick pattern trading rules. Using such strong different trading rules in which the majority of the trading signals would agree will help making the trading system very robust. Moreover, future research is encouraged to examine the candle reversal patterns in term of bullish and bearish trends. The beauty of the Japanese candlestick patterns reveals when they are used in combination with other trading rules. The key concept in using the candlestick charting system is the comprehensive technical picture of the market.

## Chapter 9

## Conclusion

## Chapter 9: Conclusion

This research attempts to examine the profitability of selected Japanese candlestick reversal patterns in the foreign exchange markets as the main objective. The research tests two null hypotheses that assume all Japanese candle reversal patterns cannot be used to forecast foreign currency price movements, and that foreign exchange markets are efficient, supporting the weak form of the EMH. The sample includes a 12-year data of 3,129 observations for seven foreign exchange currencies: AUD/USD, USD/CAD, EUR/USD, GBP/USD, USD/INR, USD/ZAR and USD/JPY. The selected Japanese candle patterns include four bullish and four bearish patterns. The bullish patterns include the bullish hammer, the piercing lines, the bullish doji star and the bullish engulfing, whereas the bearish patterns include the hanging man, the dark-cloud cover, the shooting star and the bearish engulfing. The statistical $z$ score test is used to test the average returns of open-close difference, at $5 \%$ level of significance for seven holding periods: one day, two days, three days, four days, five days, seven days and ten days. The 14-day Relative Strength Index (RSI) is used to distinguish similar patterns that appear at different turning points; these similar patterns include the bullish hammer, the hanging man and the shooting star. If the hanging man and the shooting start patterns form above 50, it is assumed that there is a high possibility that the trend will reverse from up to down. Similarly, if the bullish hammer pattern forms below the 50 reading, there is a high possibility that the current trend will reverse from down to up. To arrive to the final results that are tested statistically using z score, the number of times the candle pattern is identified ( $n$ ) has to be above 30 (Peterson and Leuthold ,1982). The second condition is that for the three candle patterns that are used in combination with the RSI filter, the results are considered only if the average returns are statistically significant at $5 \%$ level for at least five consecutive holding periods.

After examining the candle patterns in the seven currencies, the research finds evidence of some profitable of Japanese candle patterns at $5 \%$ level of significance.

Strong evidence of the bullish hammer, the bearish hanging man and the shooting star patterns in some currencies is found. The research finds that the frequency of pattern appearance for the piercing lines and the dark-cloud cover patterns are the least among the eight candle patterns. Also, the results show that the bullish hammer and the bearish hanging man patterns can be traded in AUD/USD for the first six holding periods and all the holding periods, respectively. The bearish hanging man and the shooting star patterns can be traded in USD/CAD for all the seven holding periods. The bullish hammer and the bearish hanging man patterns can be traded in EUR/USD for all the holding periods. The bullish hammer, the bearish hanging man and the shooting star patterns can be traded in GBP/USD, for the all holding periods, the first five trading periods and all the holding periods, respectively. The bullish engulfing pattern can be traded in USD/INR for all the holding periods. The bearish hanging man and the shooting star patterns can be traded in USD/ZAR for all the trading periods. Moreover, the bullish hammer, the bearish hanging man and the shooting star patterns can be traded in USD/JPY for the first five holding periods of the hanging man and all the holding periods of the other two patterns. Thus, these results reject the two null hypotheses. Furthermore, the findings of the profitable Japanese candle patterns are in line with the results found by Goo, Chen and Chang (2007); Lana, Zhanga and Xiongb (2011); Haibin, Zhao and Wang (2012); Lu, Shiu and Liu (2012) on the studies that examine the profitability of the Japanese candle patterns as technical trading rules in particular. These results also support the evidence found using other profitable technical trading rules in general by Longworth, 1981; Brock, Lakonishok and LeBaron, 1992; Gencay, 1997;Osler, 2000; Saacke, 2002; Osker, 2003, 2006; Shik and Chong, 2007; Lento and Gradojevic, 2007; Park and Scott, 2007; Stephen, 2008; Cekirdekci and Iliev, 2010 and Lönnbark and Lundström, 2012.

Market participants are recommended to use the above candle patterns in the respective foreign currency in their trading, investment and hedging decisions. It is also recommended to use the candle charts along with other trading rules, such as support and resistance levels and oscillators. For future research, it is recommended to use and
examine more sophisticated algorithm programmes and statistical models to re-test the findings of this research using both daily and intraday prices. It is also recommended to use other technical trading rules, such as support-resistance levels and oscillators, such as MACD histogram and the CCI in combination with candlestick pattern trading rules. This is required because foreign exchange markets are very complex; using such strong different trading rules makes the trading system more powerful. Moreover, future research is encouraged to examine the candle reversal patterns in term of bullish and bearish trends. The beauty of the Japanese candlestick patterns reveals when they are used in a combination with other trading rules. Last but not least, the key concept in using the candlestick charting system is the comprehensive technical picture of the market that makes these candlestick trading systems robust.

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Appendix 1: Japanese Candlestick Patterns

Below are the different types of Japanese candle patterns: reversal and continuation patterns. The number in brackets shows the number of candles required to form the pattern. (Murphy, 1999)

Bullish Reversals
Long White Body (1)
Hammer (1)
Inverted Hammer (1)
Belt Hold (1)
Engulfing Pattern (2)
Harami (2)
Harami Cross (2)
Piercing Line (2)
Doji Star (2)
Meeting Lines (2)
Three White Soldiers (3)
Morning Star (3)
Morning Doji Star (3)
Abandoned Baby (3)
Tri-Star (3)
Breakaway (5)
Three Inside Up (3)
Three Outside Up (3)
Kicking (2)
Unique Three Rivers Bottom (3)
Three Stars in the South (3)
Concealing Swallow (4)
Stick Sandwich (3)
Homing Pigeon (2)
Ladder Bottom (5)
Matching Low (2)

## Bullish Continuation

Separating Lines (2)
Rising Three Methods (5)
Upside Tasuki Gap (3)
Side by Side White Lines (3)
Three Line Strike (4)
Upside Gap Three Methods (3)
On Neck Line (2)
In Neck Line (2)

Bearish Reversals
Long Black Body (1)
Hanging Man (1)
Shooting Star (1)
Belt Hold (1)
Engulfing Pattern (2)
Harami (2)
Harami Cross (2)
Dark Cloud Cover (2)
Doji Star (2)
Meeting Lines (2)
Three Black Crows (3)
Evening Star (3)
Evening Doji Star (3)
Abandoned Baby (3)
Tri-Star (3)
Breakaway (5)
Three Inside Down (3)
Three Outside Down (3)
Kicking (2)
Latter Top (5)
Matching High (2)
Upside Gap Two Crows (3)
Identical Three Crows (3)
Deliberation (3)
Advance Block (3)
Two Crows (3)

## Bearish Continuation

Separating Lines (2)
Falling Three Methods (5)
Downside Tasuki Gap (3)
Side by Side White Lines (3)
Three Line Strike (4)
Downside Gap Three Methods (3)
On Neck Line (2)
In Neck Line (2)

Appendix 1: Japanese Candlestick Patterns (continued)


Appendix 1: Japanese Candlestick Patterns (continued)




Appendix 1: Japanese Candlestick Patterns (continued)


Appendix 1: Japanese Candlestick Patterns (continued)


Appendix 2: Descriptive statistics of the eight candle pattern analysis for AUD/USD:

| Bearish Candlestick Patterns | Descriptive Statistics | Holding Periods <br> Average | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Hanging Man | Average | 0.007 | 0.0066 | 0.0076 | 0.0082 | 0.0076 | 0.0066 | 0.0047 | 0.0063 |
|  | Var |  | 0.0001 | 0.0001 | 0.0002 | 0.0002 | 0.0002 | 0.0003 | 0.0006 |
|  | n |  | 89 | 89 | 89 | 89 | 89 | 89 | 89 |
|  | sqrit(var/n) |  | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 |
|  | Z score |  | 7.979 | 6.128 | 6.085 | 5.173 | 3.960 | 2.622 | 2.438 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
|  | SD |  | 0.008 | 0.012 | 0.013 | 0.014 | 0.016 | 0.017 | 0.025 |
|  | Min |  | -0.004 | -0.023 | -0.020 | -0.023 | -0.034 | -0.030 | -0.054 |
|  | Max |  | 0.051 | 0.073 | 0.049 | 0.053 | 0.060 | 0.058 | 0.076 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.007 | 0.0058 | 0.0069 | 0.0086 | 0.0090 | 0.0080 | 0.0059 | 0.0067 |
|  | 0.0000 | 0.0001 | 0.0002 | 0.0002 | 0.0003 | 0.0003 | 0.0005 |
|  | 57 | 57 | 57 | 57 | 57 | 57 | 57 |
|  | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.002 | 0.003 |
|  | 7.157 | 5.481 | 5.297 | 4.655 | 3.590 | 2.471 | 2.162 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 |
|  | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 |
|  | -0.003 | -0.013 | -0.014 | -0.023 | -0.034 | -0.023 | -0.035 |
|  | 0.027 | 0.031 | 0.048 | 0.053 | 0.060 | 0.058 | 0.076 |


| Dark-Cloud Cover | Average | -0.001 | 0.0002 | -0.0036 | -0.0007 | -0.0043 | 0.0004 | 0.0071 | -0.0056 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0000 | 0.0002 | 0.0003 | 0.0004 | 0.0007 | 0.0013 | 0.0011 |
|  | n |  | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
|  | sqrit(var/n) |  | 0.001 | 0.007 | 0.008 | 0.010 | 0.013 | 0.018 | 0.017 |
|  | Z score |  | 0.198 | -0.535 | -0.082 | -0.435 | 0.029 | 0.396 | -0.328 |
|  | P-value* |  | 0.42 | 0.30 | 0.47 | 0.33 | 0.49 | 0.35 | 0.37 |
|  | SD |  | 0.00 | 0.01 | 0.02 | 0.02 | 0.03 | 0.04 | 0.03 |
|  | Min |  | -0.003 | -0.020 | -0.019 | -0.025 | -0.026 | -0.027 | -0.044 |
|  | Max |  | 0.003 | 0.013 | 0.021 | 0.021 | 0.035 | 0.052 | 0.032 |


| Shooting Star | Average | 0.001 | -0.0006 | -0.0009 | -0.0009 | -0.0012 | -0.0014 | 0.0052 | 0.0038 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0002 | 0.0077 | 0.0078 |
|  | n |  | 148 | 148 | 148 | 148 | 148 | 148 | 148 |
|  | sqrit(var/n) |  | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.007 | 0.007 |
|  | Z score |  | -0.930 | -1.157 | -0.917 | -1.019 | -1.179 | 0.717 | 0.521 |
|  | P-value* |  | 0.18 | 0.12 | 0.18 | 0.15 | 0.12 | 0.24 | 0.30 |
|  | SD |  | 0.007 | 0.009 | 0.012 | 0.014 | 0.015 | 0.087 | 0.088 |
|  | Min |  | -0.025 | -0.031 | -0.051 | -0.064 | -0.053 | -0.085 | -0.062 |
|  | Max |  | 0.029 | 0.020 | 0.033 | 0.050 | 0.055 | 1.039 | 1.039 |


| 0.002 | 0.0039 | 0.0028 | 0.0022 | 0.0013 | 0.0016 | 0.0023 | 0.0025 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0.0000 | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0002 |
|  | 92 | 92 | 92 | 92 | 92 | 92 | 92 |
|  | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 |
|  | 9.602 | 4.433 | 2.319 | 1.300 | 1.573 | 2.015 | 1.553 |
|  | 0.00 | 0.00 | 0.01 | 0.10 | 0.06 | 0.02 | 0.06 |
|  | 0.004 | 0.006 | 0.009 | 0.009 | 0.010 | 0.011 | 0.015 |
|  | -0.001 | -0.010 | -0.013 | -0.025 | -0.019 | -0.018 | -0.030 |
|  | 0.019 | 0.020 | 0.051 | 0.031 | 0.031 | 0.036 | 0.059 |


| Bearish Engulfing | Average | 0.002 | -0.0015 | -0.0015 | -0.0017 | -0.0016 | -0.0021 | 0.0132 | 0.0106 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0001 | 0.0001 | 0.0002 | 0.0003 | 0.0003 | 0.0160 | 0.0163 |
|  | n |  | 70 | 70 | 70 | 70 | 70 | 70 | 70 |
|  | sqrt(var/n) |  | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.015 | 0.015 |
|  | Z score |  | -1.388 | -1.102 | -0.913 | -0.727 | -0.950 | 0.871 | 0.692 |
|  | P-value* |  | 0.08 | 0.14 | 0.18 | 0.23 | 0.17 | 0.19 | 0.24 |
|  | SD |  | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.13 | 0.13 |
|  | Min |  | -0.025 | -0.031 | -0.051 | -0.064 | -0.053 | -0.085 | -0.062 |
|  | Max |  | 0.029 | 0.020 | 0.033 | 0.050 | 0.055 | 1.039 | 1.039 |


| BullishCandlestickPatterns | Descriptive Statistics | Holding <br> Periods <br> Average | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Bullish Hammer | Average | 0.006 | 0.0054 | 0.0053 | 0.0053 | 0.0057 | 0.0055 | 0.0070 | 0.0088 |
|  | Var |  | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0003 | 0.0004 |
|  |  |  | 77 | 77 | 77 | 77 | 77 | 77 | 77 |
|  | sqrit(var/n) |  | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 |
|  | Z score |  | 9.480 | 5.729 | 5.275 | 4.439 | 3.561 | 3.500 | 4.108 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | SD |  | 0.005 | 0.008 | 0.009 | 0.011 | 0.014 | 0.018 | 0.019 |
|  | Min |  | -0.001 | -0.023 | -0.023 | -0.018 | -0.031 | -0.048 | -0.052 |
|  | Max |  | 0.034 | 0.031 | 0.022 | 0.043 | 0.040 | 0.063 | 0.070 |


| With RSI <br> Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.004 | 0.0054 | 0.0041 | 0.0030 | 0.0040 | 0.0039 | 0.0042 | 0.0051 |
|  | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0003 | 0.0003 |
|  | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
|  | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.003 |
|  | 5.895 | 2.822 | 2.101 | 2.327 | 1.886 | 1.504 | 1.742 |
|  | 0.00 | 0.00 | 0.02 | 0.01 | 0.03 | 0.07 | 0.04 |
|  | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 |
|  | -0.001 | -0.023 | -0.023 | -0.018 | -0.024 | -0.048 | -0.052 |
|  | 0.034 | 0.031 | 0.021 | 0.031 | 0.035 | 0.045 | 0.033 |


| Piercing Lines | Average | -0.005 | -0.0071 | -0.0034 | -0.0120 | -0.0059 | -0.0012 | -0.0015 | -0.0017 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0000 | 0.0001 | 0.0005 | 0.0005 | 0.0005 | 0.0005 | 0.0011 |
|  | $n$ |  | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
|  | sqrit(var/n) |  | 0.002 | 0.004 | 0.008 | 0.008 | 0.008 | 0.008 | 0.012 |
|  | Z score |  | -2.887 | -0.858 | -1.435 | -0.718 | -0.140 | -0.184 | -0.138 |
|  | P-value* |  | 0.00 | 0.20 | 0.08 | 0.24 | 0.44 | 0.43 | 0.45 |
|  | SD |  | 0.007 | 0.011 | 0.022 | 0.022 | 0.022 | 0.022 | 0.033 |
|  | Min |  | -0.018 | -0.022 | -0.041 | -0.038 | -0.026 | -0.033 | -0.049 |
|  | Max |  | 0.002 | 0.011 | 0.015 | 0.021 | 0.025 | 0.032 | 0.046 |


| Bullish Doji Star | Average | 0.004 | 0.0032 | 0.0027 | 0.0032 | 0.0038 | 0.0061 | 0.0054 | 0.0065 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0002 |
|  | n |  | 28 | 28 | 28 | 28 | 28 | 28 | 28 |
|  | sqrt(var/n) |  | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
|  | Z score |  | 3.045 | 1.903 | 1.885 | 2.206 | 2.688 | 2.326 | 2.628 |
|  | P-value* |  | 0.00 | 0.03 | 0.03 | 0.01 | 0.00 | 0.01 | 0.00 |
|  | SD |  | 0.006 | 0.007 | 0.009 | 0.009 | 0.012 | 0.012 | 0.013 |
|  | Min |  | -0.005 | -0.010 | -0.012 | -0.015 | -0.012 | -0.025 | -0.028 |
|  | Max |  | 0.014 | 0.024 | 0.022 | 0.018 | 0.050 | 0.031 | 0.026 |


| Bullish Engulfing | Average | 0.000 | -0.0005 | 0.0003 | 0.0002 | 0.0010 | 0.0011 | -0.0006 | 0.0013 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0003 | 0.0002 |
|  | n |  | 49 | 49 | 49 | 49 | 49 | 49 | 49 |
|  | sqrt(var/n) |  | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
|  | Z score |  | -0.597 | 0.243 | 0.092 | 0.586 | 0.562 | -0.258 | 0.621 |
|  | P-value* |  | 0.28 | 0.40 | 0.46 | 0.28 | 0.29 | 0.40 | 0.27 |
|  | SD |  | 0.006 | 0.010 | 0.012 | 0.012 | 0.014 | 0.016 | 0.014 |
|  | Min |  | -0.017 | -0.022 | -0.035 | -0.031 | -0.037 | -0.033 | -0.031 |
|  | Max |  | 0.012 | 0.025 | 0.025 | 0.024 | 0.031 | 0.037 | 0.032 |

Appendix 3: Descriptive statistics of the eight candle pattern analysis for USD/CAD:

| Bearish Candlestick Patterns | Descriptive Statistics | Holding Periods Average | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Hanging Man | Average | 0.006 | 0.0053 | 0.0058 | 0.0068 | 0.0063 | 0.0072 | 0.0069 | 0.0066 |
|  | Var |  | 0.0000 | 0.0000 | 0.0001 | 0.0001 | 0.0002 | 0.0003 | 0.0005 |
|  | n |  | 79 | 79 | 79 | 79 | 79 | 79 | 79 |
|  | sqrit(var/n) |  | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 |
|  | Z score |  | 11.920 | 7.456 | 6.379 | 4.888 | 4.907 | 3.632 | 2.555 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
|  | SD |  | 0.004 | 0.007 | 0.009 | 0.011 | 0.013 | 0.017 | 0.023 |
|  | Min |  | -0.001 | -0.009 | -0.015 | -0.026 | -0.023 | -0.044 | -0.090 |
|  | Max |  | 0.016 | 0.032 | 0.036 | 0.043 | 0.059 | 0.062 | 0.088 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.007 | 0.0049 | 0.0055 | 0.0077 | 0.0068 | 0.0083 | 0.0092 | 0.0087 |
|  | 0.0000 | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0003 |
|  | 44 | 44 | 44 | 44 | 44 | 44 | 44 |
|  | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.003 |
|  | 8.727 | 5.249 | 5.633 | 4.399 | 4.697 | 4.543 | 3.218 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 |
|  | 0.000 | -0.008 | -0.015 | -0.020 | -0.016 | -0.033 | -0.031 |
|  | 0.015 | 0.022 | 0.029 | 0.024 | 0.029 | 0.028 | 0.035 |


| Dark-Cloud Cover | Average | -0.001 | -0.0039 | -0.0029 | -0.0044 | -0.0040 | 0.0016 | -0.0041 | 0.0094 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0000 | 0.0003 | 0.0003 | 0.0003 | 0.0000 | 0.0002 | 0.0000 |
|  | n |  | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
|  | sqrt(var/n) |  | 0.005 | 0.012 | 0.012 | 0.012 | 0.005 | 0.010 | 0.001 |
|  | Z score |  | -0.794 | -0.250 | -0.373 | -0.331 | 0.363 | -0.411 | 9.400 |
|  | P-value* |  | 0.21 | 0.40 | 0.35 | 0.37 | 0.36 | 0.34 | 0.00 |
|  | SD |  | 0.01 | 0.02 | 0.02 | 0.02 | 0.01 | 0.01 | 0.00 |
|  | Min |  | -0.009 | -0.015 | -0.016 | -0.016 | -0.003 | -0.014 | 0.008 |
|  | Max |  | 0.001 | 0.009 | 0.007 | 0.008 | 0.006 | 0.006 | 0.010 |


| Shooting Star | Average | 0.006 | 0.0056 | 0.0055 | 0.0058 | 0.0057 | 0.0064 | 0.0068 | 0.0069 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0003 | 0.0004 |
|  | n |  | 240 | 240 | 240 | 240 | 240 | 240 | 240 |
|  | sqrt(var/n) |  | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
|  | Z score |  | 17.964 | 9.992 | 9.069 | 7.432 | 7.383 | 6.354 | 5.191 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | SD |  | 0.005 | 0.008 | 0.010 | 0.012 | 0.013 | 0.016 | 0.021 |
|  | Min |  | -0.002 | -0.024 | -0.022 | -0.024 | -0.029 | -0.046 | -0.109 |
|  | Max |  | 0.028 | 0.059 | 0.043 | 0.047 | 0.050 | 0.066 | 0.060 |


| 0.006 | 0.0064 | 0.0062 | 0.0059 | 0.0054 | 0.0053 | 0.0065 | 0.0073 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0.0000 | 0.0001 | 0.0001 | 0.0002 | 0.0002 | 0.0003 | 0.0005 |
|  | 108 | 108 | 108 | 108 | 108 | 108 | 108 |
|  | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 |
|  | 11.585 | 6.832 | 5.480 | 4.375 | 4.085 | 4.026 | 3.515 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | 0.006 | 0.009 | 0.011 | 0.013 | 0.014 | 0.017 | 0.022 |
|  | 0.000 | -0.008 | -0.022 | -0.024 | -0.029 | -0.046 | -0.109 |
|  | 0.028 | 0.059 | 0.043 | 0.046 | 0.039 | 0.066 | 0.05 |


| Bearish Engulfing | Average | 0.001 | -0.0002 | 0.0009 | 0.0003 | 0.0003 | 0.0005 | 0.0005 | 0.0020 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0001 | 0.0001 | 0.0002 | 0.0002 | 0.0003 | 0.0003 | 0.0005 |
|  | n |  | 171 | 171 | 171 | 171 | 171 | 171 | 171 |
|  | sqrt(var/n) |  | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 |
|  | 2 score |  | -0.428 | 1.065 | 0.340 | 0.237 | 0.388 | 0.367 | 1.237 |
|  | P-value* |  | 0.33 | 0.14 | 0.37 | 0.41 | 0.35 | 0.36 | 0.11 |
|  | SD |  | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 |
|  | Min |  | -0.031 | -0.033 | -0.037 | -0.035 | -0.044 | -0.054 | -0.053 |
|  | Max |  | 0.046 | 0.069 | 0.058 | 0.089 | 0.120 | 0.078 | 0.073 |


| BullishCandlestick | Descriptive Statistics | Holding <br> Periods | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Bullish Hammer | Average | 0.005 | 0.0057 | 0.0055 | 0.0054 | 0.0047 | 0.0053 | 0.0057 | 0.0052 |
|  | Var |  | 0.0000 | 0.0001 | 0.0002 | 0.0001 | 0.0003 | 0.0004 | 0.0005 |
|  | n |  | 58 | 58 | 58 | 58 | 58 | 58 | 58 |
|  | sqrt(var/n) |  | 0.001 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.003 |
|  | 2 score |  | 8.061 | 3.627 | 3.039 | 2.963 | 2.402 | 2.294 | 1.775 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.04 |
|  | SD |  | 0.005 | 0.012 | 0.014 | 0.012 | 0.017 | 0.019 | 0.022 |
|  | Min |  | 0.000 | -0.016 | -0.022 | -0.020 | -0.031 | -0.024 | -0.044 |
|  | Max |  | 0.025 | 0.043 | 0.070 | 0.043 | 0.058 | 0.072 | 0.111 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.002 | 0.0052 | 0.0026 | 0.0027 | 0.0021 | -0.0002 | 0.0014 | 0.0010 |
|  | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0002 | 0.0002 |
|  | 25 | 25 | 25 | 25 | 25 | 25 | 25 |
|  | 0.001 | 0.002 | 0.002 | 0.002 | 0.003 | 0.003 | 0.003 |
|  | 6.554 | 1.535 | 1.686 | 1.112 | -0.076 | 0.517 | 0.347 |
|  | 0.00 | 0.06 | 0.05 | 0.13 | 0.47 | 0.30 | 0.36 |
|  | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
|  | 0.000 | -0.016 | -0.010 | -0.010 | -0.031 | -0.024 | -0.022 |
|  | 0.013 | 0.025 | 0.021 | 0.030 | 0.025 | 0.027 | 0.043 |


|  | Average |  | 0.0055 | 0.0055 | 0.0080 | 0.0058 | 0.0075 | 0.0116 | 0.0160 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0000 | 0.0001 | 0.0003 | 0.0001 | 0.0003 | 0.0008 | 0.0006 |
|  | n |  | 8 | 8 | 8 | 8 | 8 | 8 | 8 |
|  | sqrit(var/n) |  | 0.002 | 0.003 | 0.006 | 0.004 | 0.006 | 0.010 | 0.009 |
| Piercing Lines | Z score | 0.009 | 3.026 | 1.927 | 1.333 | 1.358 | 1.298 | 1.182 | 1.811 |
|  | P-value* |  | 0.00 | 0.03 | 0.09 | 0.09 | 0.10 | 0.12 | 0.04 |
|  | SD |  | 0.005 | 0.008 | 0.017 | 0.012 | 0.016 | 0.028 | 0.025 |
|  | Min |  | -0.005 | -0.009 | -0.010 | -0.008 | -0.012 | -0.035 | -0.015 |
|  | Max |  | 0.013 | 0.015 | 0.039 | 0.030 | 0.037 | 0.044 | 0.058 |


| Bullish Doji Star | Average | 0.004 | 0.0007 | 0.0034 | 0.0055 | 0.0036 | 0.0043 | 0.0044 | 0.0077 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0001 | 0.0002 | 0.0003 | 0.0002 | 0.0003 | 0.0005 | 0.0009 |
|  | n |  | 19 | 19 | 19 | 19 | 19 | 19 | 19 |
|  | sqrt(var/n) |  | 0.002 | 0.003 | 0.004 | 0.003 | 0.004 | 0.005 | 0.007 |
|  | Z score |  | 0.382 | 1.158 | 1.275 | 1.115 | 1.085 | 0.882 | 1.133 |
|  | P-value* |  | 0.35 | 0.12 | 0.10 | 0.13 | 0.14 | 0.19 | 0.13 |
|  | SD |  | 0.008 | 0.013 | 0.019 | 0.014 | 0.017 | 0.022 | 0.030 |
|  | Min |  | -0.013 | -0.016 | -0.030 | -0.028 | -0.026 | -0.035 | -0.036 |
|  | Max |  | 0.025 | 0.043 | 0.070 | 0.043 | 0.058 | 0.072 | 0.111 |


| Bullish Engulfing | Average | -0.002 | -0.0014 | -0.0025 | -0.0014 | -0.0023 | -0.0008 | -0.0011 | -0.0034 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0003 | 0.0002 |
|  | n |  | 35 | 35 | 35 | 35 | 35 | 35 | 35 |
|  | sqrit(var/n) |  | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.003 | 0.003 |
|  | Z score |  | -1.851 | -1.755 | -0.847 | -1.241 | -0.409 | -0.375 | -1.343 |
|  | P-value* |  | 0.03 | 0.04 | 0.20 | 0.11 | 0.34 | 0.35 | 0.09 |
|  | SD |  | 0.005 | 0.008 | 0.010 | 0.011 | 0.011 | 0.017 | 0.015 |
|  | Min |  | -0.012 | -0.026 | -0.024 | -0.024 | -0.034 | -0.042 | -0.034 |
|  | Max |  | 0.009 | 0.012 | 0.024 | 0.019 | 0.018 | 0.030 | 0.027 |

Appendix 4: Descriptive statistics of the eight candle pattern analysis for EUR/USD:

| Bearish Candlestick Patterns | Descriptive Statistics | Holding Periods Average | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Hanging Man | Average | 0.005 | 0.0060 | 0.0063 | 0.0053 | 0.0044 | 0.0035 | 0.0046 | 0.0043 |
|  | Var |  | 0.0000 | 0.0001 | 0.0002 | 0.0002 | 0.0003 | 0.0004 | 0.0006 |
|  | n |  | 106 | 106 | 106 | 106 | 106 | 106 | 106 |
|  | sqrt(var/n) |  | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 |
|  | Z score |  | 11.057 | 6.201 | 4.199 | 3.044 | 2.185 | 2.435 | 1.841 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.03 |
|  | SD |  | 0.006 | 0.011 | 0.013 | 0.015 | 0.016 | 0.019 | 0.024 |
|  | Min |  | -0.004 | -0.021 | -0.022 | -0.036 | -0.035 | -0.031 | -0.085 |
|  | Max |  | 0.029 | 0.032 | 0.038 | 0.044 | 0.043 | 0.058 | 0.061 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.005 | 0.0058 | 0.0072 | 0.0049 | 0.0054 | 0.0048 | 0.0046 | 0.0039 |
|  | 0.0000 | 0.0001 | 0.0001 | 0.0002 | 0.0003 | 0.0003 | 0.0004 |
|  | 57 | 57 | 57 | 57 | 57 | 57 | 57 |
|  | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.002 | 0.003 |
|  | 7.749 | 5.822 | 3.207 | 2.860 | 2.254 | 2.000 | 1.476 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 0.07 |
|  | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 |
|  | -0.002 | -0.012 | -0.018 | -0.024 | -0.032 | -0.025 | -0.034 |
|  | 0.029 | 0.032 | 0.038 | 0.044 | 0.043 | 0.053 | 0.047 |


| Dark-Cloud Cover | Average | -0.004 | 0.0004 | -0.0009 | -0.0024 | -0.0043 | -0.0081 | -0.0047 | -0.0059 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0002 | 0.0001 | 0.0003 | 0.0003 | 0.0003 | 0.0004 | 0.0005 |
|  | n |  | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
|  | sqrt(var/n) |  | 0.005 | 0.004 | 0.006 | 0.007 | 0.007 | 0.008 | 0.008 |
|  | Z score |  | 0.094 | -0.229 | -0.386 | -0.623 | -1.190 | -0.613 | -0.735 |
|  | P-value* |  | 0.46 | 0.59 | 0.65 | 0.73 | 0.88 | 0.73 | 0.77 |
|  | SD |  | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
|  | Min |  | -0.020 | -0.009 | -0.028 | -0.025 | -0.027 | -0.025 | -0.025 |
|  | Max |  | 0.018 | 0.017 | 0.020 | 0.026 | 0.018 | 0.030 | 0.032 |



| 0.021 | 0.0064 | 0.0054 | 0.0216 | 0.0202 | 0.0218 | 0.0359 | 0.0360 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0.0000 | 0.0001 | 0.0201 | 0.0202 | 0.0203 | 0.0398 | 0.0399 |
|  | 87 | 87 | 87 | 87 | 87 | 87 | 87 |
|  | 0.001 | 0.001 | 0.015 | 0.015 | 0.015 | 0.021 | 0.021 |
|  | 9.528 | 4.571 | 1.422 | 1.327 | 1.431 | 1.678 | 1.681 |
|  | 0.00 | 0.00 | 0.08 | 0.09 | 0.08 | 0.05 | 0.05 |
|  | 0.006 | 0.011 | 0.142 | 0.142 | 0.142 | 0.199 | 0.200 |
|  | -0.001 | -0.022 | -0.023 | -0.024 | -0.027 | -0.036 | -0.048 |
|  | 0.033 | 0.052 | 1.323 | 1.323 | 1.323 | 1.323 | 1.323 |


| Bearish Engulfing | Average | 0.001 | 0.0006 | 0.0007 | 0.0010 | 0.0016 | 0.0016 | 0.0012 | 0.0000 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0001 | 0.0002 | 0.0002 | 0.0002 | 0.0003 | 0.0004 | 0.0007 |
|  | n |  | 156 | 156 | 156 | 156 | 156 | 156 | 156 |
|  | sqrit(var/n) |  | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 |
|  | Z score |  | 0.748 | 0.671 | 0.852 | 1.316 | 1.188 | 0.707 | 0.002 |
|  | P-value* |  | 0.23 | 0.25 | 0.20 | 0.09 | 0.12 | 0.24 | 0.50 |
|  | SD |  | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 |
|  | Min |  | -0.022 | -0.031 | -0.030 | -0.041 | -0.035 | -0.041 | -0.066 |
|  | Max |  | 0.030 | 0.039 | 0.053 | 0.043 | 0.050 | 0.071 | 0.080 |


| BullishCandlestick | Descriptive Statistics | Holding Periods | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Bullish Hammer | Average | 0.010 | 0.0069 | 0.0085 | 0.0103 | 0.0097 | 0.0082 | 0.0111 | 0.0137 |
|  | Var |  | 0.0000 | 0.0001 | 0.0002 | 0.0002 | 0.0003 | 0.0004 | 0.0008 |
|  | n |  | 64 | 64 | 64 | 64 | 64 | 64 | 64 |
|  | sqrt(var/n) |  | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.003 | 0.003 |
|  | Z score |  | 9.122 | 5.806 | 5.359 | 5.122 | 3.939 | 4.311 | 3.942 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | SD |  | 0.006 | 0.012 | 0.015 | 0.015 | 0.017 | 0.021 | 0.028 |
|  | Min |  | 0.000 | -0.009 | -0.012 | -0.020 | -0.036 | -0.031 | -0.039 |
|  | Max |  | 0.034 | 0.073 | 0.103 | 0.084 | 0.055 | 0.067 | 0.170 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.009 | 0.0064 | 0.0080 | 0.0094 | 0.0085 | 0.0060 | 0.0108 | 0.0162 |
|  | 0.0000 | 0.0001 | 0.0001 | 0.0002 | 0.0003 | 0.0005 | 0.0010 |
|  | 34 | 34 | 34 | 34 | 34 | 34 | 34 |
|  | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.004 | 0.005 |
|  | 7.655 | 5.739 | 5.329 | 3.898 | 2.012 | 2.946 | 3.011 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 |
|  | 0.00 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 |
|  | 0.001 | -0.004 | -0.007 | -0.016 | -0.036 | -0.025 | -0.031 |
|  | 0.020 | 0.028 | 0.032 | 0.032 | 0.043 | 0.067 | 0.170 |



Appendix 5: Descriptive statistics of the eight candle pattern analysis for GBP/USD:

| Bearish Candlestick Patterns | Descriptive Statistics | Holding Periods Average | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Hanging Man | Average | 0.006 | 0.0067 | 0.0061 | 0.0053 | 0.0049 | 0.0054 | 0.0065 | 0.0058 |
|  | Var |  | 0.0000 | 0.0002 | 0.0002 | 0.0003 | 0.0004 | 0.0008 | 0.0011 |
|  | n |  | 99 | 99 | 99 | 99 | 99 | 99 | 99 |
|  | sqrit(var/n) |  | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.003 | 0.003 |
|  | Z score |  | 10.008 | 4.341 | 3.443 | 2.727 | 2.588 | 2.316 | 1.757 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 |
|  | SD |  | 0.007 | 0.014 | 0.015 | 0.018 | 0.021 | 0.028 | 0.033 |
|  | Min |  | -0.001 | -0.019 | -0.028 | -0.052 | -0.063 | -0.070 | -0.071 |
|  | Max |  | 0.039 | 0.078 | 0.057 | 0.063 | 0.063 | 0.109 | 0.124 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.005 | 0.0061 | 0.0055 | 0.0052 | 0.0053 | 0.0057 | 0.0048 | 0.0027 |
|  | 0.0000 | 0.0001 | 0.0002 | 0.0003 | 0.0004 | 0.0007 | 0.0010 |
|  | 57 | 57 | 57 | 57 | 57 | 57 | 57 |
|  | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.004 | 0.004 |
|  | 7.854 | 3.929 | 2.641 | 2.212 | 2.127 | 1.368 | 0.651 |
|  | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 0.09 | 0.26 |
|  | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.03 |
|  | -0.001 | -0.015 | -0.026 | -0.052 | -0.063 | -0.070 | -0.071 |
|  | 0.031 | 0.045 | 0.057 | 0.063 | 0.057 | 0.081 | 0.124 |


| Dark-Cloud Cover | Average | -0.001 | 0.0014 | 0.0033 | 0.0006 | -0.0084 | -0.0093 | 0.0030 | 0.0053 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | N/A | N/A | N/A | N/A | N/A | N/A | N/A |
|  | n |  | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
|  | sqrit(var/n) |  | N/A | N/A | N/A | N/A | N/A | N/A | N/A |
|  | 2 score |  | N/A | N/A | N/A | N/A | N/A | N/A | N/A |
|  | P-value* |  | N/A | N/A | N/A | N/A | N/A | N/A | N/A |
|  | SD |  | N/A | N/A | N/A | N/A | N/A | N/A | N/A |
|  | Min |  | 0.001 | 0.003 | 0.001 | -0.008 | -0.009 | 0.003 | 0.005 |
|  | Max |  | 0.001 | 0.003 | 0.001 | -0.008 | -0.009 | 0.003 | 0.005 |


| Shooting Star | Average | 0.013 | 0.0076 | 0.0083 | 0.0079 | 0.0157 | 0.0170 | 0.0178 | 0.0196 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0001 | 0.0002 | 0.0003 | 0.0136 | 0.0137 | 0.0138 | 0.0142 |
|  | n |  | 197 | 197 | 197 | 197 | 197 | 197 | 197 |
|  | sqrit(var/n) |  | 0.001 | 0.001 | 0.001 | 0.008 | 0.008 | 0.008 | 0.008 |
|  | Z score |  | 14.462 | 8.325 | 6.124 | 1.888 | 2.040 | 2.118 | 2.304 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.03 | 0.02 | 0.02 | 0.01 |
|  | SD |  | 0.007 | 0.014 | 0.018 | 0.116 | 0.117 | 0.118 | 0.119 |
|  | Min |  | -0.009 | -0.026 | -0.048 | -0.061 | -0.054 | -0.065 | -0.079 |
|  | Max |  | 0.037 | 0.093 | 0.088 | 1.614 | 1.614 | 1.614 | 1.614 |


| 0.010 | 0.0086 | 0.0100 | 0.0096 | 0.0083 | 0.0102 | 0.0100 | 0.0117 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0.0001 | 0.0003 | 0.0004 | 0.0006 | 0.0009 | 0.0010 | 0.0014 |
|  | 93 | 93 | 93 | 93 | 93 | 93 | 93 |
|  | 0.001 | 0.002 | 0.002 | 0.003 | 0.003 | 0.003 | 0.004 |
|  | 9.759 | 5.952 | 4.630 | 3.246 | 3.344 | 3.118 | 3.013 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | 0.008 | 0.016 | 0.020 | 0.025 | 0.029 | 0.031 | 0.037 |
|  | -0.007 | -0.026 | -0.043 | -0.051 | -0.054 | -0.047 | -0.070 |
|  | 0.037 | 0.093 | 0.088 | 0.097 | 0.107 | 0.117 | 0.151 |


| Bearish Engulfing | Average | 0.009 | 0.0004 | 0.0003 | 0.0130 | 0.0132 | 0.0125 | 0.0112 | 0.0127 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0001 | 0.0003 | 0.0200 | 0.0201 | 0.0202 | 0.0204 | 0.0208 |
|  | n |  | 131 | 131 | 131 | 131 | 131 | 131 | 131 |
|  | sqrit(var/n) |  | 0.001 | 0.001 | 0.012 | 0.012 | 0.012 | 0.012 | 0.013 |
|  | 2 score |  | 0.427 | 0.200 | 1.053 | 1.063 | 1.007 | 0.898 | 1.005 |
|  | P-value* |  | 0.33 | 0.42 | 0.15 | 0.14 | 0.16 | 0.18 | 0.16 |
|  | SD |  | 0.01 | 0.02 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 |
|  | Min |  | -0.027 | -0.041 | -0.042 | -0.056 | -0.059 | -0.075 | -0.097 |
|  | Max |  | 0.055 | 0.067 | 1.610 | 1.610 | 1.610 | 1.610 | 1.610 |


| Bullish Candlestick | Descriptive Statistics | Holding Periods | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Bullish <br> Hammer | Average | 0.007 | 0.0070 | 0.0061 | 0.0054 | 0.0066 | 0.0086 | 0.0079 | 0.0080 |
|  | Var |  | 0.0000 | 0.0001 | 0.0002 | 0.0003 | 0.0004 | 0.0006 | 0.0009 |
|  | $n$ |  | 97 | 97 | 97 | 97 | 97 | 97 | 97 |
|  | sqrit(var/n) |  | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.003 |
|  | Z score |  | 12.056 | 5.534 | 3.889 | 3.736 | 4.265 | 3.309 | 2.568 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
|  | SD |  | 0.006 | 0.011 | 0.014 | 0.017 | 0.020 | 0.024 | 0.031 |
|  | Min |  | -0.002 | -0.019 | -0.024 | -0.032 | -0.036 | -0.043 | -0.119 |
|  | Max |  | 0.028 | 0.042 | 0.049 | 0.058 | 0.078 | 0.088 | 0.108 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.011 | 0.0088 | 0.0098 | 0.0090 | 0.0123 | 0.0141 | 0.0132 | 0.0120 |
|  | 0.0000 | 0.0001 | 0.0002 | 0.0003 | 0.0004 | 0.0007 | 0.0012 |
|  | 37 | 37 | 37 | 37 | 37 | 37 | 37 |
|  | 0.001 | 0.002 | 0.002 | 0.003 | 0.003 | 0.004 | 0.006 |
|  | 8.059 | 5.146 | 3.929 | 4.206 | 4.140 | 3.036 | 2.071 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
|  | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.04 |
|  | -0.001 | -0.011 | -0.020 | -0.032 | -0.036 | -0.043 | -0.119 |
|  | 0.028 | 0.042 | 0.049 | 0.058 | 0.078 | 0.088 | 0.108 |


| Piercing Lines | Average | -0.006 | -0.0011 | 0.0063 | -0.0025 | -0.0111 | -0.0083 | -0.0198 | -0.0086 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0002 | 0.0007 | 0.0011 | 0.0022 | 0.0021 | 0.0051 | 0.0014 |
|  | n |  | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
|  | sqrt(var/n) |  | 0.006 | 0.010 | 0.013 | 0.018 | 0.017 | 0.027 | 0.014 |
|  | Z score |  | -0.194 | 0.628 | -0.192 | -0.626 | -0.486 | -0.736 | -0.605 |
|  | P-value* |  | 0.42 | 0.27 | 0.42 | 0.27 | 0.31 | 0.23 | 0.27 |
|  | SD |  | 0.015 | 0.026 | 0.034 | 0.047 | 0.045 | 0.071 | 0.038 |
|  | Min |  | -0.018 | -0.026 | -0.063 | -0.102 | -0.099 | -0.178 | -0.088 |
|  | Max |  | 0.024 | 0.054 | 0.043 | 0.047 | 0.047 | 0.034 | 0.021 |


| Bullish Doji Star | Average | -0.003 | -0.0013 | 0.0003 | -0.0017 | -0.0042 | -0.0036 | -0.0049 | -0.0070 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0001 | 0.0001 | 0.0002 | 0.0003 | 0.0008 | 0.0011 | 0.0020 |
|  | n |  | 17 | 17 | 17 | 17 | 17 | 17 | 17 |
|  | sqrit(var/n) |  | 0.002 | 0.003 | 0.003 | 0.005 | 0.007 | 0.008 | 0.011 |
|  | Z score |  | -0.562 | 0.106 | -0.559 | -0.930 | -0.519 | -0.618 | -0.649 |
|  | P-value* |  | 0.29 | 0.46 | 0.29 | 0.18 | 0.30 | 0.27 | 0.26 |
|  | SD |  | 0.009 | 0.011 | 0.012 | 0.019 | 0.028 | 0.033 | 0.045 |
|  | Min |  | -0.024 | -0.021 | -0.025 | -0.049 | -0.073 | -0.109 | -0.149 |
|  | Max |  | 0.009 | 0.015 | 0.023 | 0.020 | 0.026 | 0.027 | 0.040 |


| Bullish <br> Engulfing | Average | 0.002 | 0.0010 | 0.0020 | 0.0031 | 0.0038 | 0.0018 | -0.0009 | 0.0043 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0001 | 0.0002 | 0.0003 | 0.0003 | 0.0004 | 0.0006 | 0.0008 |
|  | n |  | 48 | 48 | 48 | 48 | 48 | 48 | 48 |
|  | sqrit(var/n) |  | 0.002 | 0.002 | 0.003 | 0.003 | 0.003 | 0.004 | 0.004 |
|  | Z score |  | 0.622 | 0.980 | 1.203 | 1.505 | 0.648 | -0.253 | 1.057 |
|  | P-value* |  | 0.27 | 0.16 | 0.11 | 0.07 | 0.26 | 0.40 | 0.15 |
|  | SD |  | 0.011 | 0.014 | 0.018 | 0.018 | 0.020 | 0.025 | 0.028 |
|  | Min |  | -0.024 | -0.026 | -0.044 | -0.036 | -0.057 | -0.066 | -0.085 |
|  | Max |  | 0.031 | 0.044 | 0.044 | 0.049 | 0.037 | 0.058 | 0.084 |

Appendix 6: Descriptive statistics of the eight candle pattern analysis for USD/INR:

| Bearish <br> Candlestick <br> Patterns | Descriptive Statistics | Holding Periods Average | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Hanging Man | Average | 0.083 | 0.0878 | 0.0685 | 0.0760 | 0.0671 | 0.0864 | 0.1322 | 0.0653 |
|  | Var |  | 0.0250 | 0.0591 | 0.0938 | 0.1514 | 0.2612 | 0.3663 | 0.3983 |
|  | n |  | 69 | 69 | 69 | 69 | 69 | 69 | 69 |
|  | sqrt(var/n) |  | 0.019 | 0.029 | 0.037 | 0.047 | 0.062 | 0.073 | 0.076 |
|  | Z score |  | 4.611 | 2.342 | 2.060 | 1.432 | 1.405 | 1.814 | 0.859 |
|  | P-value* |  | 0.00 | 0.01 | 0.02 | 0.08 | 0.08 | 0.03 | 0.20 |
|  | SD |  | 0.158 | 0.243 | 0.306 | 0.389 | 0.511 | 0.605 | 0.631 |
|  | Min |  | -0.150 | -0.560 | -0.870 | -1.200 | -1.510 | -1.300 | -1.500 |
|  | Max |  | 0.790 | 0.880 | 0.900 | 1.500 | 1.790 | 2.470 | 2.090 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.095 | 0.0978 | 0.0930 | 0.0774 | 0.0790 | 0.0750 | 0.1638 | 0.0823 |
|  | 0.0374 | 0.0726 | 0.1313 | 0.2246 | 0.3039 | 0.4316 | 0.4429 |
|  | 39 | 39 | 39 | 39 | 39 | 39 | 39 |
|  | 0.031 | 0.043 | 0.058 | 0.076 | 0.088 | 0.105 | 0.107 |
|  | 3.156 | 2.155 | 1.334 | 1.041 | 0.850 | 1.558 | 0.772 |
|  | 0.00 | 0.02 | 0.09 | 0.15 | 0.20 | 0.06 | 0.22 |
|  | 0.19 | 0.27 | 0.36 | 0.47 | 0.55 | 0.66 | 0.67 |
|  | -0.140 | -0.560 | -0.870 | -1.200 | -1.510 | -1.300 | -1.500 |
|  | 0.790 | 0.880 | 0.900 | 1.500 | 1.620 | 2.470 | 1.825 |


| Dark-Cloud Cover | Average | 0.033 | 0.0050 | -0.0150 | -0.0250 | 0.0450 | 0.0500 | 0.0750 | 0.0950 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0000 | 0.0001 | 0.0005 | 0.0004 | 0.0002 | 0.0004 | 0.0005 |
|  | n |  | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
|  | sqrit(var/n) |  | 0.005 | 0.005 | 0.015 | 0.015 | 0.010 | 0.015 | 0.015 |
|  | Z score |  | 1.000 | -3.000 | -1.667 | 3.000 | 5.000 | 5.000 | 6.333 |
|  | P-value* |  | 0.16 | 0.00 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | SD |  | 0.01 | 0.01 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 |
|  | Min |  | 0.000 | -0.020 | -0.040 | 0.030 | 0.040 | 0.060 | 0.080 |
|  | Max |  | 0.010 | -0.010 | -0.010 | 0.060 | 0.060 | 0.090 | 0.110 |



| -0.122 | -0.0865 | -0.1014 | -0.1246 | -0.1153 | -0.1164 | -0.1473 | -0.1630 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 8.1040 | 8.1589 | 8.1685 | 8.1601 | 8.2796 | 8.2566 | 8.3881 |
|  | 244 | 244 | 244 | 244 | 244 | 244 | 244 |
|  | 0.182 | 0.183 | 0.183 | 0.183 | 0.184 | 0.184 | 0.185 |
|  | -0.474 | -0.554 | -0.681 | -0.630 | -0.632 | -0.801 | -0.879 |
|  | 0.32 | 0.29 | 0.25 | 0.26 | 0.26 | 0.21 | 0.19 |
|  | 2.847 | 2.856 | 2.858 | 2.857 | 2.877 | 2.873 | 2.896 |
|  | -44.310 | -44.390 | -44.340 | -44.100 | -44.290 | -44.240 | -44.420 |
|  | 1.150 | 1.470 | 1.590 | 2.760 | 2.790 | 2.050 | 2.300 |


| Bearish Engulfing | Average | 0.950 | 0.0273 | 0.9833 | 0.9691 | 0.9676 | 0.9295 | 0.8935 | 1.8775 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0406 | 54.7179 | 54.7892 | 54.8641 | 55.0897 | 55.2705 | 107.6427 |
|  | n |  | 55 | 55 | 55 | 55 | 55 | 55 | 55 |
|  | sqrt(var/n) |  | 0.027 | 0.997 | 0.998 | 0.999 | 1.001 | 1.002 | 1.399 |
|  | Z score |  | 1.003 | 0.986 | 0.971 | 0.969 | 0.929 | 0.891 | 1.342 |
|  | P-value* |  | 0.16 | 0.16 | 0.17 | 0.17 | 0.18 | 0.19 | 0.09 |
|  | SD |  | 0.20 | 7.40 | 7.40 | 7.41 | 7.42 | 7.43 | 10.38 |
|  | Min |  | -0.500 | -0.750 | -1.010 | -0.930 | -1.800 | -1.630 | -1.370 |
|  | Max |  | 0.790 | 54.800 | 54.800 | 54.800 | 54.800 | 54.800 | 54.800 |


| BullishCandlestick | Descriptive Statistics | Holding Periods | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Bullish Hammer | Average | 0.183 | 0.1364 | 0.1059 | 0.1434 | 0.1296 | 0.2064 | 0.2481 | 0.3112 |
|  | Var |  | 0.0210 | 0.0518 | 0.1254 | 0.2227 | 0.2393 | 0.3067 | 0.5032 |
|  | n |  | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
|  | sqrit(var/n) |  | 0.023 | 0.036 | 0.056 | 0.075 | 0.077 | 0.088 | 0.112 |
|  | Z score |  | 5.948 | 2.943 | 2.562 | 1.737 | 2.669 | 2.834 | 2.775 |
|  | P-value* |  | 0.00 | 0.00 | 0.01 | 0.04 | 0.00 | 0.00 | 0.00 |
|  | SD |  | 0.145 | 0.228 | 0.354 | 0.472 | 0.489 | 0.554 | 0.709 |
|  | Min |  | -0.090 | -0.370 | -0.340 | -0.720 | -0.660 | -0.910 | -1.650 |
|  | Max |  | 0.670 | 0.660 | 1.070 | 1.355 | 1.440 | 1.750 | 2.360 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.157 | 0.1450 | 0.0992 | 0.0837 | 0.1100 | 0.1362 | 0.2317 | 0.2908 |
|  | 0.0112 | 0.0486 | 0.0968 | 0.2973 | 0.2659 | 0.2819 | 0.2750 |
|  | 12 | 12 | 12 | 12 | 12 | 12 | 12 |
|  | 0.031 | 0.064 | 0.090 | 0.157 | 0.149 | 0.153 | 0.151 |
|  | 4.743 | 1.558 | 0.932 | 0.699 | 0.915 | 1.511 | 1.921 |
|  | 0.00 | 0.06 | 0.18 | 0.24 | 0.18 | 0.07 | 0.03 |
|  | 0.11 | 0.22 | 0.31 | 0.55 | 0.52 | 0.53 | 0.52 |
|  | -0.030 | -0.370 | -0.240 | -0.720 | -0.580 | -0.460 | -0.290 |
|  | 0.340 | 0.505 | 0.815 | 1.355 | 1.265 | 1.250 | 1.340 |



Appendix 7: Descriptive statistics of the eight candle pattern analysis for USD/JPY:

| Bullish Doji Star | Average | -0.077 | 0.0712 | -0.0032 | 0.0100 | -0.0100 | -0.0524 | -0.2624 | -0.2920 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.2879 | 0.3971 | 0.6164 | 1.2216 | 1.6133 | 2.6647 | 4.5166 |
|  | n |  | 25 | 25 | 25 | 25 | 25 | 25 | 25 |
|  | sqrt(var/n) |  | 0.107 | 0.126 | 0.157 | 0.221 | 0.254 | 0.326 | 0.425 |
|  | Z score |  | 0.664 | -0.025 | 0.064 | -0.045 | -0.206 | -0.804 | -0.687 |
|  | P-value* |  | 0.25 | 0.49 | 0.47 | 0.48 | 0.42 | 0.21 | 0.25 |
|  | SD |  | 0.537 | 0.630 | 0.785 | 1.105 | 1.270 | 1.632 | 2.125 |
|  | Min |  | -1.680 | -1.890 | -1.980 | -3.480 | -3.600 | -3.740 | -4.560 |
|  | Max |  | 1.140 | 1.050 | 1.780 | 2.400 | 2.740 | 2.590 | 3.550 |



| Bullish Engulfing | Average | 0.039 | -0.0151 | -0.0058 | 0.1167 | -0.0253 | 0.0518 | 0.0553 | 0.0973 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.3934 | 0.6098 | 1.0455 | 1.4099 | 1.7290 | 2.2702 | 2.6855 |
|  | n |  | 45 | 45 | 45 | 45 | 45 | 45 | 45 |
|  | sqrit(var/n) |  | 0.094 | 0.116 | 0.152 | 0.177 | 0.196 | 0.225 | 0.244 |
|  | Z score |  | -0.162 | -0.050 | 0.765 | -0.143 | 0.264 | 0.246 | 0.398 |
|  | P-value* |  | 0.44 | 0.48 | 0.22 | 0.44 | 0.40 | 0.40 | 0.35 |
|  | SD |  | 0.627 | 0.781 | 1.022 | 1.187 | 1.315 | 1.507 | 1.639 |
|  | Min |  | -2.020 | -1.640 | -1.840 | -3.270 | -2.550 | -3.270 | -3.360 |
|  | Max |  | 1.350 | 1.930 | 2.250 | 2.260 | 2.700 | 3.280 | 3.800 |


| Bearish Candlestick Patterns | Descriptive Statistics | Holding Periods Average | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Hanging Man | Average | 0.582 | 0.4627 | 0.4714 | 0.4714 | 0.4802 | 0.4465 | 0.5732 | 1.1671 |
|  | Var |  | 0.2363 | 0.7149 | 1.3438 | 1.5472 | 2.1160 | 2.8719 | 48.8549 |
|  | n |  | 155 | 155 | 155 | 155 | 155 | 155 | 155 |
|  | sqrt(var/n) |  | 0.039 | 0.068 | 0.093 | 0.100 | 0.117 | 0.136 | 0.561 |
|  | Z score |  | 11.851 | 6.941 | 5.063 | 4.806 | 3.822 | 4.211 | 2.079 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
|  | SD |  | 0.486 | 0.846 | 1.159 | 1.244 | 1.455 | 1.695 | 6.990 |
|  | Min |  | -0.260 | -1.240 | -2.580 | -3.470 | -4.190 | -3.010 | -3.720 |
|  | Max |  | 3.730 | 5.210 | 4.350 | 5.260 | 4.710 | 5.770 | 84.360 |


| Dark-Cloud Cover | Average | 0.297 | 0.5050 | 0.2725 | 0.2975 | 0.1250 | 0.0200 | 0.1800 | 0.6800 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.1947 | 1.4612 | 4.1297 | 2.0731 | 4.0901 | 8.5650 | 8.2270 |
|  | n |  | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
|  | sqrt(var/n) |  | 0.221 | 0.604 | 1.016 | 0.720 | 1.011 | 1.463 | 1.434 |
|  | Z score |  | 2.289 | 0.451 | 0.293 | 0.174 | 0.020 | 0.123 | 0.474 |
|  | P-value* |  | 0.01 | 0.33 | 0.38 | 0.43 | 0.49 | 0.45 | 0.32 |
|  | SD |  | 0.44 | 1.21 | 2.03 | 1.44 | 2.02 | 2.93 | 2.87 |
|  | Min |  | -0.040 | -1.320 | -2.180 | -1.620 | -2.420 | -3.330 | -3.290 |
|  | Max |  | 0.950 | 1.280 | 2.570 | 1.850 | 2.520 | 3.300 | 3.100 |


| Shooting Star | Average | 0.554 | 0.5516 | 0.5495 | 0.5417 | 0.5094 | 0.5444 | 0.5442 | 0.6372 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.2540 | 0.6708 | 1.1223 | 1.5253 | 1.9160 | 2.9185 | 3.4308 |
|  | n |  | 190 | 190 | 190 | 190 | 190 | 190 | 190 |
|  | sqrit(var/n) |  | 0.037 | 0.059 | 0.077 | 0.090 | 0.100 | 0.124 | 0.134 |
|  | Z score |  | 15.089 | 9.247 | 7.049 | 5.685 | 5.421 | 4.391 | 4.742 |
|  | P -value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | SD |  | 0.504 | 0.819 | 1.059 | 1.235 | 1.384 | 1.708 | 1.852 |
|  | Min |  | -0.130 | -1.320 | -2.180 | -3.600 | -4.150 | -3.330 | -3.760 |
|  | Max |  | 2.680 | 4.170 | 4.210 | 4.790 | 5.130 | 5.810 | 6.580 |


| 0.635 | 0.5869 | 0.6464 | 0.6567 | 0.6036 | 0.6421 | 0.5719 | 0.7360 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0.3170 | 0.9840 | 1.3320 | 2.0250 | 2.4616 | 2.9482 | 3.0796 |
|  | 75 | 75 | 75 | 75 | 75 | 75 | 75 |
|  | 0.065 | 0.115 | 0.133 | 0.164 | 0.181 | 0.198 | 0.203 |
|  | 9.029 | 5.643 | 4.928 | 3.673 | 3.544 | 2.884 | 3.632 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | 0.563 | 0.992 | 1.154 | 1.423 | 1.569 | 1.717 | 1.755 |
|  | -0.110 | -1.200 | -1.470 | -3.600 | -4.150 | -3.300 | -3.760 |
|  | 2.680 | 4.170 | 4.210 | 4.790 | 4.530 | 5.810 | 4.820 |


| Bearish Engulfing | Average | 0.115 | -0.0060 | 0.0189 | 0.1251 | 0.1894 | 0.1125 | 0.1518 | 0.2117 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.4819 | 0.8791 | 1.5597 | 2.0948 | 2.1718 | 2.8314 | 3.8831 |
|  | n |  | 181 | 181 | 181 | 181 | 181 | 181 | 181 |
|  | sqrt(var/n) |  | 0.052 | 0.070 | 0.093 | 0.108 | 0.110 | 0.125 | 0.146 |
|  | Z score |  | -0.117 | 0.271 | 1.348 | 1.761 | 1.027 | 1.213 | 1.445 |
|  | P-value* |  | 0.45 | 0.39 | 0.09 | 0.04 | 0.15 | 0.11 | 0.07 |
|  | SD |  | 0.69 | 0.94 | 1.25 | 1.45 | 1.47 | 1.68 | 1.97 |
|  | Min |  | -1.880 | -2.970 | -2.760 | -3.470 | -3.690 | -3.850 | -4.420 |
|  | Max |  | 3.360 | 2.640 | 6.200 | 7.680 | 4.080 | 5.490 | 5.600 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.334 | 0.4929 | 0.4990 | 0.5166 | 0.4418 | 0.3647 | -0.0148 | 0.0368 |
|  | 0.1684 | 0.6561 | 1.2318 | 1.4783 | 2.5952 | 3.3189 | 4.8136 |
|  | 62 | 62 | 62 | 62 | 62 | 62 | 62 |
|  | 0.052 | 0.103 | 0.141 | 0.154 | 0.205 | 0.231 | 0.279 |
|  | 9.457 | 4.851 | 3.665 | 2.861 | 1.782 | -0.064 | 0.132 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 0.47 | 0.45 |
|  | 0.41 | 0.81 | 1.11 | 1.22 | 1.61 | 1.82 | 2.19 |
|  | -0.040 | -1.280 | -3.770 | -3.800 | -7.360 | -4.810 | -4.990 |
|  | 1.520 | 2.670 | 2.960 | 2.540 | 3.120 | 3.130 | 4.480 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.656 | 0.3676 | 0.3777 | 0.3810 | 0.4011 | 0.5360 | 0.7405 | 1.7862 |
|  | 0.1087 | 0.4250 | 1.0271 | 1.3060 | 1.8991 | 2.8927 | 88.8050 |
|  | 82 | 82 | 82 | 82 | 82 | 82 | 82 |
|  | 0.036 | 0.072 | 0.112 | 0.126 | 0.152 | 0.188 | 1.041 |
|  | 10.095 | 5.246 | 3.404 | 3.178 | 3.522 | 3.942 | 1.716 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 |
|  | 0.33 | 0.65 | 1.01 | 1.14 | 1.38 | 1.70 | 9.42 |
|  | -0.260 | -0.750 | -2.580 | -3.470 | -4.190 | -3.010 | -3.720 |
|  | 1.220 | 2.010 | 3.320 | 2.990 | 4.710 | 5.770 | 84.360 |



| Piercing Lines | Average | 0.107 | 0.297 | 0.563 | -0.032 | -0.018 | -0.037 | -0.153 | 0.130 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.259 | 0.265 | 0.314 | 0.544 | 0.770 | 3.447 | 7.578 |
|  | n |  | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
|  | sqrt(var/n) |  | 0.254 | 0.257 | 0.280 | 0.369 | 0.439 | 0.928 | 1.376 |
|  | Z score |  | 1.17 | 2.19 | -0.12 | -0.05 | -0.09 | -0.16 | 0.09 |
|  | P-value* |  | 0.121 | 0.014 | 0.454 | 0.481 | 0.466 | 0.435 | 0.462 |
|  | SD |  | 0.508 | 0.514 | 0.560 | 0.738 | 0.878 | 1.857 | 2.753 |
|  | Min |  | -0.140 | 0.000 | -0.680 | -0.660 | -0.740 | -2.390 | -3.950 |
|  | Max |  | 0.990 | 1.160 | 0.550 | 0.980 | 1.170 | 1.740 | 1.800 |

Appendix 8: Descriptive statistics of the eight candle pattern analysis for USD/ZAR:

| Bearish Candlestick Patterns | Descriptive Statistics | Holding Periods Average | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Hanging Man | Average | 0.045 | 0.0612 | 0.0633 | 0.0436 | 0.0500 | 0.0405 | 0.0355 | 0.0221 |
|  | Var |  | 0.0051 | 0.0115 | 0.0404 | 0.0311 | 0.0371 | 0.0634 | 0.1094 |
|  | n |  | 123 | 123 | 123 | 123 | 123 | 123 | 123 |
|  | sqrit(var/n) |  | 0.006 | 0.010 | 0.018 | 0.016 | 0.017 | 0.023 | 0.030 |
|  | Z score |  | 9.486 | 6.547 | 2.408 | 3.143 | 2.333 | 1.564 | 0.742 |
|  | P-value* |  | 0.00 | 0.00 | 0.01 | 0.00 | 0.01 | 0.06 | 0.23 |
|  | SD |  | 0.072 | 0.107 | 0.201 | 0.176 | 0.193 | 0.252 | 0.331 |
|  | Min |  | -0.017 | -0.193 | -1.491 | -0.776 | -0.771 | -1.411 | -1.956 |
|  | Max |  | 0.386 | 0.591 | 0.756 | 0.701 | 0.711 | 1.041 | 1.245 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.052 | 0.0640 | 0.0753 | 0.0492 | 0.0552 | 0.0488 | 0.0499 | 0.0218 |
|  | 0.0061 | 0.0145 | 0.0606 | 0.0420 | 0.0478 | 0.0830 | 0.1432 |
|  | 71 | 71 | 71 | 71 | 71 | 71 | 71 |
|  | 0.009 | 0.014 | 0.029 | 0.024 | 0.026 | 0.034 | 0.045 |
|  | 6.891 | 5.276 | 1.682 | 2.272 | 1.879 | 1.459 | 0.486 |
|  | 0.00 | 0.00 | 0.05 | 0.01 | 0.03 | 0.07 | 0.31 |
|  | 0.08 | 0.12 | 0.25 | 0.20 | 0.22 | 0.29 | 0.38 |
|  | -0.016 | -0.193 | -1.491 | -0.776 | -0.771 | -1.411 | -1.956 |
|  | 0.386 | 0.591 | 0.756 | 0.701 | 0.711 | 1.041 | 1.245 |


| Dark-Cloud Cover | Average | 0.121 | -0.0173 | 0.0100 | 0.2250 | 0.1815 | 0.1525 | 0.1356 | 0.1625 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0008 | 0.0060 | 0.0300 | 0.0186 | 0.0015 | 0.0310 | 0.0630 |
|  | n |  | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
|  | sqrt(var/n) |  | 0.020 | 0.055 | 0.123 | 0.097 | 0.027 | 0.124 | 0.178 |
|  | 2 score |  | -0.878 | 0.182 | 1.837 | 1.881 | 5.545 | 1.090 | 0.915 |
|  | P-value ${ }^{\text {* }}$ |  | 0.81 | 0.43 | 0.03 | 0.03 | 0.00 | 0.14 | 0.18 |
|  | SD |  | 0.03 | 0.08 | 0.17 | 0.14 | 0.04 | 0.18 | 0.25 |
|  | Min |  | -0.037 | -0.045 | 0.103 | 0.085 | 0.125 | 0.011 | -0.015 |
|  | Max |  | 0.002 | 0.065 | 0.348 | 0.278 | 0.180 | 0.260 | 0.340 |


| Shooting Star | Average | 0.109 | 0.0629 | 0.0639 | 0.0647 | 0.1014 | 0.1293 | 0.1668 | 0.1766 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0029 | 0.0130 | 0.0261 | 0.2831 | 0.5460 | 0.8072 | 0.8148 |
|  | n |  | 282 | 282 | 282 | 282 | 282 | 282 | 282 |
|  | sqrt(var/n) |  | 0.003 | 0.007 | 0.010 | 0.032 | 0.044 | 0.054 | 0.054 |
|  | Z score |  | 19.658 | 9.415 | 6.726 | 3.200 | 2.939 | 3.118 | 3.286 |
|  | P-value* |  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | SD |  | 0.054 | 0.114 | 0.161 | 0.532 | 0.739 | 0.898 | 0.903 |
|  | Min |  | -0.040 | -0.290 | -0.601 | -0.610 | -1.325 | -1.310 | -1.175 |
|  | Max |  | 0.363 | 0.930 | 1.380 | 8.521 | 8.523 | 8.531 | 8.531 |


| 0.066 | 0.0650 | 0.0596 | 0.0633 | 0.0707 | 0.0639 | 0.0715 | 0.0689 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0.0035 | 0.0181 | 0.0321 | 0.0364 | 0.0561 | 0.0624 | 0.0686 |
|  | 129 | 129 | 129 | 129 | 129 | 129 | 129 |
|  | 0.005 | 0.012 | 0.016 | 0.017 | 0.021 | 0.022 | 0.023 |
|  | 12.478 | 5.039 | 4.010 | 4.212 | 3.064 | 3.252 | 2.987 |
|  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
|  | 0.059 | 0.134 | 0.179 | 0.191 | 0.237 | 0.250 | 0.262 |
|  | -0.040 | -0.290 | -0.395 | -0.610 | -1.325 | -1.310 | -1.175 |
|  | 0.363 | 0.930 | 1.380 | 1.285 | 1.390 | 1.480 | 1.033 |


| Bearish Engulfing | Average | 0.002 | 0.0006 | 0.0056 | 0.0022 | 0.0018 | -0.0057 | -0.0049 | 0.0112 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Var |  | 0.0085 | 0.0214 | 0.0259 | 0.0296 | 0.0422 | 0.0481 | 0.0671 |
|  | n |  | 129 | 129 | 129 | 129 | 129 | 129 | 129 |
|  | sart(var/n) |  | 0.008 | 0.013 | 0.014 | 0.015 | 0.018 | 0.019 | 0.023 |
|  | Z score |  | 0.070 | 0.435 | 0.155 | 0.118 | -0.315 | -0.255 | 0.489 |
|  | P-value* |  | 0.47 | 0.33 | 0.44 | 0.45 | 0.62 | 0.60 | 0.31 |
|  | SD |  | 0.09 | 0.15 | 0.16 | 0.17 | 0.21 | 0.22 | 0.26 |
|  | Min |  | -0.419 | -0.541 | -0.538 | -0.708 | -1.298 | -1.078 | -1.248 |
|  | Max |  | 0.440 | 0.762 | 0.590 | 0.610 | 0.408 | 0.650 | 0.780 |


| Bullish Candlestick | Descriptive Statistics | Holding Periods | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| Bullish <br> Hammer | Average | 0.090 | 0.0810 | 0.0799 | 0.0903 | 0.0956 | 0.1014 | 0.0867 | 0.0925 |
|  | Var |  | 0.0328 | 0.0205 | 0.0284 | 0.0330 | 0.0525 | 0.0750 | 0.0827 |
|  | n |  | 85 | 85 | 85 | 85 | 85 | 85 | 85 |
|  | sqrt(var/n) |  | 0.020 | 0.016 | 0.018 | 0.020 | 0.025 | 0.030 | 0.031 |
|  | Z score |  | 4.123 | 5.140 | 4.944 | 4.852 | 4.078 | 2.919 | 2.965 |
|  | P-value* |  | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
|  | SD |  | 0.181 | 0.143 | 0.168 | 0.182 | 0.229 | 0.274 | 0.288 |
|  | Min |  | -0.025 | -0.162 | -0.339 | -0.222 | -0.270 | -0.242 | -0.361 |
|  | Max |  | 1.590 | 0.875 | 0.870 | 1.030 | 1.510 | 1.920 | 1.120 |


| With RSI Filter | Holding period |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 Day | 2 Days | 3 Days | 4 Days | 5 Days | 7 Days | 10 Days |
| 0.066 | 0.0467 | 0.0517 | 0.0632 | 0.0622 | 0.0693 | 0.0713 | 0.0956 |
|  | 0.0012 | 0.0124 | 0.0213 | 0.0191 | 0.0221 | 0.0396 | 0.0595 |
|  | 41 | 41 | 41 | 41 | 41 | 41 | 41 |
|  | 0.005 | 0.017 | 0.023 | 0.022 | 0.023 | 0.031 | 0.038 |
|  | 8.579 | 2.970 | 2.772 | 2.882 | 2.983 | 2.296 | 2.511 |
|  | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.99 | 0.99 |
|  | 0.03 | 0.11 | 0.15 | 0.14 | 0.15 | 0.20 | 0.24 |
|  | 0.000 | -0.120 | -0.172 | -0.222 | -0.270 | -0.190 | -0.301 |
|  | 0.153 | 0.590 | 0.683 | 0.510 | 0.520 | 0.670 | 0.640 |



