

Technical analysis in the foreign exchange market: the case of the MACD (Moving Average Convergence Divergence) indicator

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Biography

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Sumário

O objetivo deste estudo é analisar a previsibilidade do indicador de análise técnica, Moving Average Convergence Divergence (MACD), para o período 1994-2016, como ferramenta de negociação aplicada ao mercado de divisas. Analisamos um conjunto de pares de moedas, nomeadamente, o Dólar Australiano face ao Dólar Neozelandês, o Dólar Australiano face ao Dólar Americano, o Dólar Canadiano face ao Franco Suíço e a Libra Esterlina face ao Iene Japonês. O algoritmo utilizado tem por base a identificação da divergência entre o preço do activo e o valor do indicador, indicando a direção da ordem a executar. Analisamos estratégias alternativas de investimento, em particular, portfólios *Carry Trade*. Em termos gerais, o conjunto de parâmetros [19,39] providencia os melhores resultados em termos de retorno líquido e factor de recuperação e é superior ao portefólio *Carry Trade* em termos de retorno ajustado ao risco (rácio remuneração/risco), mas nem sempre em termos de eficiência (rácio de Sharpe).

Palavras-chave: Indicadores de Análise Técnica, MACD, Mercado de Divisas

Códigos-JEL: F31, G11, G14, G23

Abstract

The intent of this study is to analyze the predictability of the technical indicator Moving Average Convergence Divergence (MACD), for the period 1994-2016, as a tool of foreign exchange trading. We applied it to a set of major and minor currency pairs, namely, Australian Dollar versus New Zealand Dollar, Australian Dollar versus United Sates Dollar, Canadian Dollar versus Swiss Franc and British Pound versus Japanese Yen. We set an algorithm to identify the divergence between the asset's price and the indicator's value, giving the trading order's direction. Additionally, we evaluate alternative active and passive strategies such as the portfolio *Carry Trade* strategy. Overall, the results show that the [19,39] set dominates in terms of net returns and recovery factor and is superior to the *Carry Trade* strategy in risk-adjusted terms (reward/risk ratio) but not always on efficiency terms (Sharpe ratio).

Key-words: Technical Indicator, MACD, Foreign Exchange

JEL-Codes: F31, G11, G14, G23

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Glossary

Term	Definition
A booking system	System employed by brokers that act just as intermediaries, sending their clients' trading orders directly to liquidity providers or multilateral trading facilities
B booking system	System employed by brokers who keep their clients' orders internally
Base currency	The first currency that appears in a currency pair quote
Candlestick	Japanese-type of chart that shows the opening, high, low and close prices of a tradable asset for an interval of time
Counter currency	The second currency that appears in a currency pair quote
Drawdown	Biggest drop in value of an investment in an asset from its peak to its trough
Electronic Communication Network (ECN)	Automated electronic system that matches buy and sell orders
Expert advisor (EA)	Program intended to automate the trading actions of an investor for the Metatrader platform
Harami pattern	Candlestick chart pattern in which a large candlestick is followed by a smaller candlestick body, which should be located within the former's candlestick price range
Islamic account	Free-swap account
Moving Average Convergence Divergence (MACD)	Trend and momentum technical indicator which depicts the relationship between two moving averages of price for different lengths
Metatrader 4	Electronic trading platform used mainly for foreign exchange trading
MQL4	Programming language used to develop programs for Metatrader 4
MQL5	Programming language used to develop programs for Metatrader 5

Multilateral trading facilities (MTFs)	Non-regulated exchanges used for foreign exchange trading
Non dealing desk (NDD)	Broker that provides direct access to the interbank market
Pip	The minimum change in value between two currencies
Point and Figure Chart	Type of price-dependent chart represented by rising X-Columns and falling O-Columns
Slippage	Difference between the price a trader expects and the one he actually gets
Standard lot	Lot comprising 100,000 monetary units
Straight Through Processing (STP)	System of fully automation of orders in the interbank market with no broker intervention
Swap/Rollover fee	Overnight gain/loss deposited/charged by brokers on a client's account, depending on the market and broker's conditions
Virtual Private Server	Type of virtual service provided by an internet hosting service

1 Introduction

Based on the Monetary and Economic department of the Bank for International Settlements (BIS, 2016), foreign exchange turnover, as of April 2016, accounted for 5.1 trillion dollars a day. The supply and demand for forex market-related instruments turned it into a massive open market. The major segments in the foreign exchange market are: spot transactions, outright forwards, foreign exchange swaps, currency swaps and options.

Since the 90s, the foreign exchange market have suffered extreme changes, mainly due to the impact of "other financial institutions" as referred by King and Rime (2010). These institutions are asset managers and institutional investors, but also include smaller banks, mutual funds, money market funds, insurance firms, pension funds, hedge funds and central banks. Also, high-frequency trading is considered to be a relevant and constant source of foreign exchange turnover, accounting for at least 35% of foreign exchange algorithmic trading (King, Osler and Rime, 2011). According to the data, from April, 2013 to April, 2016, there was a decrease of over 5% in over-the-counter (OTC) foreign exchange turnover and there was also a decline of spot turnover for the first time since 2001. Yet the amount traded in 2016 is 4 times compared to 2001, for both cases. In terms of countries, as of April 2016, the United Kingdom, the United States, Singapore, Hong Kong SAR, and Japan accounted for 77% of foreign exchange trading, comparatively to 75% and 71% in April, 2013 and April, 2010, respectively. In 2016, spot foreign exchange trading accounted for almost 33% of all instruments available for trading currencies (BIS, 2016).

In terms of forex trading pairs, the US dollar remains the powerhouse currency as it is used in 88% of all spot transactions (2016). The euro and the yen are used in 31% and 22% of all foreign exchanges transactions (2016), respectively.

In terms of currency tradable instruments, some changes occurred as a consequence of the financial markets progress. Even though the spot market is still a highly relevant type of transaction, since 1995 forex swaps have overcome spot trading in terms of global turnover. In terms of growth, outright forwards, foreign exchange swaps and currency swaps remain at the top with a positive growth of 439%, 263% and 1071%, respectively, since 2001.

In the 90s, financial companies have begun developing electronic trading platforms for forex trading. Financial institutions developed the main systems, the request-for-quote (RFQ) service and the pre-trade anonymous limit order book. 360 Trading Networks and Thomson Reuters Matching are the mainstream platforms as of today. These two platforms provide all the most used currency-related tradable support instruments to institutional investors like spot, forwards, non-deliverable forwards (NDFs), options and swaps trading.

As electronic trading evolved, retail traders have become involved in currency trading as well and regulation have been adapted to serve every party. As a consequence, some countries, namely the USA and Japan have drastically reduced the leverage levels allowed to 50:1 and 25:1, respectively (Maitra, 2014). However, in Europe, there are some trading firms that offer leverage up to 1000:1.

Currently, retail traders can also take advantage of a new feature introduced by trading firms, which is called social trading. In practical terms, traders can copy each other's orders in a fully automated way, when there are any signal providers available (Corp., 2016).

This dissertation attempts to evaluate trading strategies based upon a technical analysis tool that has not been extensively examined, in particular, on what refers to its application to the foreign exchange market, the Moving Average Convergence Divergence (MACD).

While there are several models and theories proposed within the technical analysis framework, there is no convincing evidence of a simple and a statistically significant predictive tool. As such, we propose a simple trading system which prompts the user to buy or sell foreign currency, based on the signals generated by the MACD.

The primary purpose of the study is, thus, to find out if the MACD's signals are able to predict a determined currency pair's price direction, dependent on a specific time frame and predetermined set of parameters. The MACD algorithm is applied using the MT4 platform's price data, for daily and weekly time frames.

According to our results, the different sets of parameters present rather distinct results. Nonetheless, the [19,39] set of parameters, used to compute the MACD indicator, can provide

the best alternative in terms of net returns, risk-adjusted returns (reward/risk ratio) and strategy's stability (Sharpe ratio).

Regarding the structure of the dissertation, Chapter 2 gives an overview of the technical analysis field and its main tools, and includes a review of related studies, in particular with regard to foreign exchange predictability and trading strategies based upon. Chapter 3 provides the description of the proposed methodology and how it is applied to different sets of price data. Chapter 4 presents the results and statistical tests. Finally, we draw the main conclusions and also stress the main limitations of the research work and provide ideas for future research.

2 Literature Review: Empirical evidence

2.1 Technical Analysis and Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis states that prices incorporate and reflect all information, thus, it is impossible to beat the market. The EMH is traditionally divided in three forms: weak, semi-strong and strong forms.

Technical analysis is the process through which investors gather past price- and volume-based data in order to predict future prices. Evidence that trading strategies based upon technical analysis can obtain excess returns contradict the EMH in its weak form.

The technical analysis impact on financial traders has been reported by Taylor and Allen (1992) research: dating back from 1988, at least 90% of the people polled by the Bank of England, referred that technical analysis had some influence on their trading decisions for different time frames. They do posit that traders' decisions in the short-term were heavily dependent on technical analysis.

In this chapter, we address the mainstream financial theories and others not yet accepted or underestimated due to its complexity. We discuss, in particular, MACD's results and implementation issues.

2.1.1 Previous studies: the 60s and 70s

In the presence of speculative markets, according to a study by Alexander (1961), prices support the random walk hypothesis, however, in the presence of a definite price direction, the movement tends to subsist. This particular movement, is considered to be more substantial when the price change varies between 5 and 30 percent. So, he concludes that, in fact, trends exist, but there is a doubt regarding its effectiveness if it turns out to be ubiquitous. However, a research conducted by Fama and Blume (1966), analyzing the results provided by Alexander (1961) in the stock market, using price variation filters, for the period 1897-1959, for the DJIA Index, in fact, cannot produce profits above the buy-and-hold strategy, even when one disregards the presence of transaction costs and commissions. They also stress the presence of a bias related to the use of price indexes, which make the dividends' adjustment rather difficult (1928-1961).

More evidence against Alexander's results is provided by Mandelbrot (1963), who asserts that an investor using the filters' strategy would enter the market above the filter's hit rule in a long position and vice versa, an occurrence which Alexander understates. As such, the critic claims that Alexander returns are overstated in the best case scenario whereas in the worst case scenario his returns can turn out to be the result of emphasizing rapid price changes.

As of the 1970s, the concept of data snooping was still at a fledgling stage and Jensen and Benington (1970) dubbed it as selection bias. In this particular instance, the referred snooping bias analysis occur for investigations led by Levy (1967a) and Levy (1967b). According to his results, he posits that, since stock prices follow predictable trends, the random walk hypotheses is not suitable to address financial markets. Jensen and Benington (1970), perform the same analysis, but for a different interval (1926-1966) and different number of stocks (1952) as opposed to the interval 1960-1965 and 200 stocks, respectively. They conclude that for their chosen period, there is no evidence that Levi's two trading rules work, being that when transaction costs are considered, the trading rules do not perform much better, and are riskier, than the buy-and-hold strategy for the monthly closing prices of the New York Stock Exchange stocks. In fact, when adjusted for risk, both trading rules yield negative returns when compared to the buy-and-hold strategy.

Previously, Jensen (1967) had already stressed the refutability of Levi's results as well as four main issues that remain unanalyzed. The main subjective points against Levy's results are the following: the random selection policy; the risk adjustment properties derived from trading rules; the returns that appear to be the result of luck rather than to be derived from economic theories or models; and the fact that orders are executed at Friday's closing price.

Given the fledgling state of processes and underdevelopment of sound financial theories in the 60s and 70s, the following authors proceed with much thorough analyzes.

2.1.2 Previous studies: the 70s to the Present

The seminal work provided by Malkiel and Fama (1970), an empirical analysis of stock market prices' predictability, sustains that the efficient market hypothesis (EMH) holds.

Based on weekly data, returns do not exhibit serial correlation, providing no ground for profitable strategies based on historical prices.

Using a genetic algorithm applied to the S&P 500 for the test period 1970-1989 with 82 different trading rules, Allen and Karjalainen (1999) find that it is possible to obtain an average excess return of 4.51% above the annual buy-and-hold return of 6.72%. On the other hand, according to the authors, only institutional investors would be able to trade using the referred trading rules due to intraday timing of trading signals, the occurrence of erratic dividend policies, and the fact that the algorithm parameters are still not optimal.

Ratner and Leal (1999) use the bootstrapping methodology, to analyze the results of applying 10 Variable Length Moving Average (VMA) models, on a set of 10 emerging equity stock markets in Latin America and Asia. They find that Taiwan turns out to be the one which possesses the highest first order serial correlation and the one with the lowest trading costs. Overall, the trading models do not yield profitable returns for most emerging markets.

Brock, Lakonishok, and LeBaron (1992) test the predictability of stock returns, using the moving average and trading range break strategies, for the Dow Jones index for the period 1897-1986. They find that the technical indicators have predictive power, but stress that transaction costs would have to be taken into account before using them. Also, they find that buy signals produce higher returns than sell signals and exhibit lower volatility in the market afterwards.

Contrarily to Brock et al. (1992) findings, Ready (2002) finds out that their results come from choosing popular technical trading rules used in the 1980s, and due to the snooping bias. Besides that, after 1986 (last year under analysis), the rules seem to produce returns below the buy-and-hold strategy. On the other hand, performing a comparative analysis of the trading rules used by both Brock et al. (1992) and Allen and Karjalainen (1999), the author concludes that once one had the trading rules and did not have any prior knowledge of whether they would work or not, one would not obtain returns above the buy-and-hold strategy.

Another cohort of detractors of Brock et al. (1992) work practices are Bessembinder and Chan (1998), who posit that the supposed predictive ability of the technical indicators occur as a consequence, partly, of nonsynchronous trading leading to errors when measuring the returns.

Differently, Sullivan, Timmermann, and White (1999) find out that the results of Brock et al. (1992) pass the test regarding the presence of data snooping bias for the period 1897-1986 as well as for all the four sub-periods. They show there are even more profitable trading rules than the ones presented by Brock et al. (1992). A further investigation into the data snooping issues is also approached by Lo and MacKinlay (1990), stressing the fact that "… the nature of these violations is often as subtle as it is profound". To test for the presence of the referred bias, they use the Reality Check bootstrap methodology provided by White (2000). They conclude that the random walk model null hypothesis has no superior predictive power than the benchmark strategy. On the other hand, they find that the technical rules employed for the 90-year period, in economic terms, do not yield statistically significant results.

A thorough study conducted by Payne (2003), in the currency market, for the USD/DEM (US Dollar/Deutsche Mark) pair, finds out that, in fact, past trades contain relevant information. The author spots the presence of asymmetric information of around 60% embedded in the bid-ask spread of Reuters D2000-2 system and up to 40% in the pair's price movement is the consequence of order flows. Also, using the VAR model, they conclude that the variation in liquidity levels cause the variation of the asymmetric information coefficients.

Once again, raising awareness to the market efficiency matter, Malkiel (2003) and Grossman and Stiglitz (1980), state that due to some participants' irrationality, some anomalies can happen, namely predictable price patterns that can be present for long periods of time. Moreover, they posit that markets cannot be totally efficient, because otherwise, investors would not be interested in being involved, case in which all information would be fully reflected in prices at every moment in time. An enlightening statement is also unraveled by Grossman and Stiglitz (1980), who state: "Undoubtedly, with the passage of time and with increasing sophistication of our databases and empirical techniques, we will document

further apparent departures from efficiency and further patterns in the development of stock returns".

Regarding the random walk hypothesis, also presented by Malkiel (2003), and described by himself as a price series for which there is no serial correlation, characterizes it as process through which the information is instantly reflected in stock prices. Given the erratic movement of prices, it is assumed that each day's price movement is a result of the current day events and not due to any other reasons. And, as he assumes, "news is by definition unpredictable, and, thus, resulting price changes must be unpredictable and random".

Using a simple volatility-based specification test, Lo and MacKinlay (1988) analyze weekly stock returns for all stocks from the CRSP database, for the period 1962-1985, and reject the random walk hypothesis. Succinctly, the random walk hypothesis is contradicted by the weekly returns stochastic behavior, specifically for small cap stocks. On the other hand, their work contradicts Fama and French (1988) findings of negative autocorrelation for the period 1926-1985. The former authors find a positive autocorrelation for weekly and monthly holding-period returns. Nonetheless, the authors stress the fact that, even though the random walk hypothesis is rejected, it does not mean that there is any type of inefficiency in the stock market price movements.

Concluding, even though some authors such as Alexander (1961) and Brock et al. (1992) portray results against market efficiency, others, such as Ready (2002) and Bessembinder and Chan (1998) reach opposite conclusions, suggesting that the market is not inefficient as the former suggest.

2.2 Candlestick patterns

2.2.1 Candlestick's definition

A candlestick is a price formation based on the open, high, low and close values and represented as a candle. The candlestick's hollow or filled part is the "body" and the up and lower lines of the body are the "shadows" or "wicks". The maximum of the shadow is the interval's high whereas the minimum of the shadow is the interval's low. Their inexistence, means the high is equal to the close and the low equal to the open in the presence of a hollow

body and vice versa for a filled body. Usually, if the closing price is higher than the opening price, the candle has a hollow or white body. On the other hand, if the closing price is lower than the opening price the candle as a full (filled) black body. In practical terms, white candlesticks indicate a buying tendency and black candlesticks indicate a selling tendency. Moreover, the longer the candlestick's body, the higher the buying and selling tendency, for a white and black bodies, respectively.

In terms of complexity, there is a huge set of candlestick formations that a trader can take advantage of, and, depending on his own view, he can opt for the ones he considers to be more statistically consistent or that fit his trading strategies and risk appetite. For a simpler approach, there is the possibility of blending two candles, by using the open of the first candlestick and the close of the following candlestick and pick the highest high and lowest low values of the two, simultaneously, to match the set of candles or get close to an already defined pattern.

Nowadays, with the technology development at full tilt, brokers' platforms provide very accessible and straightforward software, which allows the trader to act on a split second once he is accustomed to the underlying technique. Visually, it is possible to detect the type of candlestick and the market's tendency for a determined time frame and act accordingly.

2.2.2 Candlesticks' origin

Candlestick patterns debut in non-electronically financial markets occurred in the 17th century in Japan. However, the most prominent character, Munehisa Homma, who started trading rice futures at the Dojima Rice Exchange in Osaka, Japan, in 1750, achieved this status due to a set of systems implemented by himself. The ones used were a record of yearly weather conditions and a communications system with men placed on rooftops to send signals with flags to the exchange. Besides that, he owned a rice farm, which allowed him to have privileged information about the rice market. Simultaneously, he conducted thorough analyses of rice price movements that dated back to the late 1600s, when the rice market was still located at Yodoya's yard, a merchant's front yard (Nison, 1991).

Like bar charts, candlestick charts represent a remarkably designed approach offered to market participants for trading liquid financial market assets. Even though traders have started using bar charts and point and figure charts for almost a century, candlestick charts, which were already available in the Orient, only become available after some time in the Occident (Nison, 1994).

The candle chart's major advocate and also the one that brought the technical analysis system to the West, Steve Nison, argues that the technique provides a lot more information to traders than more recently West-developed charts. According to his studies, he claims that candle charts protract the ongoing supply and demand faced by investors, it shows the asset's trend, but also its force, contrarily to chart patterns and it allows traders to better time their trades due to swifter patterns' formations. Moreover, he firmly states that every trader should use candle charts because they include all the information present in bar charts, namely trading signals and at the same time the practitioner can take advantage of the earlier reversal signals provided by the candles (Nison, 2003).

Perhaps, the most distinguishable feature of candle charts, is the easiness to interpret them and draw fast-paced conclusions regarding the market's sentiment. In simple terms, an enlarged candle's body gives information regarding an expected upward (standard white body) or downward (standard black body) movement. On the other hand, small bodies represent standstill situations, referring to instances where traders are unsure of the market's direction.

2.2.3 Candlestick analysis profitability

After Steve Nison's studies emerged in the West, practitioners and scholars became aware that a new technique could be the tool that could allow someone to beat the market consistently. Also, if usable and profitable, it would question the Efficient Market Hypothesis (EMH).

Marshall, Young, and Rose (2006), for a set of 35 stocks of the Dow Jones Industrial Average (DJIA) US index, over the period from January, 1992 to December, 2002, analyze the profitability of candlestick trading strategies, using an extension of a bootstrap methodology.

By using this methodology, the authors are able to generate random open, high, low and close (OHLC) prices, as suggested by Efron and Tibshirani (1986) to create different price series. The period under analysis was carefully chosen because the DJIA index was only created in 1986 and could not be traded before. A possibility to circumvent this restriction would be buying each stock according to DJIA main feature, since it is a price-weighted index. Besides that, a regular adjustment had to be done in order to respect the index composition's method. They remove single lines and patterns with no explanatory power and the ones that occurred infrequently. As a consequence, from the initial 18 single lines and 44 patterns, the analysis is conducted based on only 14 single lines and 14 patterns.

Regarding the bootstrapping method, Marshall, Young, and Rose (2006) state that, contrarily to *t*-statistics that cannot account for the main stock return data, the former method can do it. In order to fit the data, it is chosen a set of four different null models, but it is the GARCH-in-mean model the one used to analyze the results, as it is the most used by other authors under similar circumstances.

One of main contributions of this investigation was the introduction, for the first time, of the OHLC price system, whereas in the past, investigators only used the close prices when testing trading strategies.

The authors use a holding period comprised of ten days[1], but hold the opened position until maturity, regardless of any other contrary pattern formed in the meantime, for the current position. Also, even though they use signals at close *t*, close *t*+1, and open *t*+1, the main results obtained through the bootstrap methodology come from opening a position in the day after which the signal was formed, at the opening price.

The results are mixed. While the bullish signals' results are unexpected, the bearish signals' results are as expected. For bullish signals, the trader profits less than half of the time, and

[1] Morris (2006) considers that candlestick analysis is best suited for short-term trading, more precisely for a ten-day period. As such, his methodology is based on a 10-day holding period and on a 10-day exponential moving average to detect the preceding trend.

for bearish signals, the trader profits more than half of the time. Some signals result in large losses and, as a direct consequence, the average daily profit/loss is negative.

On the other hand, authors find that all single bullish lines present higher returns when the bootstrap method is used and for the 28 patterns analyzed, 22 produce no statistically significant *p*-values for any stock of the DJIA.

Based on Marshall et al. (2006) findings, it is concluded that the selected candlestick patterns have no price predictive power, when using the bootstrap methodology, supporting the efficient market hypothesis (EMH).

Caginalp and Laurent (1998) study the S&P 500 Index stocks and all the worldwide closed-end funds, from 1992 to 1996, to test the predictability of candlestick reversal patterns. Different from previous studies, they perform out-of-sample tests for the referred period using Morris (2006) set of patterns. According to their results, the three-day pattern strategies can forecast price direction, either using buy or sell signals, being that the former result in higher returns. For a two-day average holding period, profits amount to roughly 1%. When reversals happen, prices tend to move higher (bullish reversal) and vice versa.

Using 59 stocks from the TOPIX Large 70 and 41 stocks from the TOPIX Mid 400 indexes, from 1975 to 2004, Marshall, Young, and Cahan (2008) exploit the predictability of candlestick analysis. Their strategy takes the opening price in the day after the signal, holding the position for 10 days. The prior trend takes a 10-day EMA. Regarding the methodology, the authors use the bootstrapping GARCH-in-mean (GARCH-M) model as Marshall et al. (2006) do, and the same signals. In the 2008 research, the authors find 206711 signals out of 83220 OHLC and similarly to the 2006 study, find no predictive value in candlestick analysis performed for the Japan's main stock exchange, not even before transaction costs.

Confirming Caginalp and Laurent (1998) findings, Lu, Shiu, and Liu (2012) study three bullish and three bearish reversals signals (Morris, 1992), in the Taiwan Top 50 Tracker fund, from October 29, 2002 to 2008, applying two-day candlestick patterns and holding the positions until a contrary pattern occurs. They find that, bullish reversal patterns have higher predictive power than bearish signals. Also, contrarily to former studies, the authors use a

variable holding period and do not employ stop-loss trading strategies nor technical indicators, simultaneously. According to their findings, the method employed provides positive returns after transactions costs.

In another research, using the Taiwan Top 50 Tracker Fund and the Taiwan Mid-Cap 100 Tracker Fund, from 1997 to 2006, using daily data of 25 stocks, Goo, Chen, and Chang (2007) find that candlestick analysis have predictive value. One of the main innovations is the introduction of a stop-loss, being that out of the different possibilities tested, i.e., 5%, 7% and 10%, the 5% stop-loss level is the most effective due to the improved mean rate return followed by candlestick patterns. Another finding, is that different candlestick formations must be followed by orders with different holdings periods. Then, (reversal) bullish candlestick formations should have longer holding periods whereas (reversal) bearish candlestick formations should have shorter holding periods. In essence, (reversal) bullish candlesticks perform better than (reversal) bearish candlesticks, being that the reversal bullish signals provide the highest return of all possibilities. They conclude that, contrarily to Marshall et al. (2006), evidence suggests that the Taiwan stock markets are inefficient.

Further results about candlestick reversals signals are provided by Lu and Shiu (2011), who posit that the harami pattern (large body followed by a small body within the previous candle's body) presents the highest predictive power in the Taiwan stock market for the 1998-2007 interval. Specifically, the bullish harami forecasting ability is enhanced for 4 and 5-day holding periods and the bearish harami forecasting ability is enhanced for 1 to 5-day holding periods. Comparatively, this research has set forward some basic criteria to improve the overall trading strategies using candlesticks, namely the holding period for each pattern, the gap between the two bodies and the impact of volume.

Recently, Lu and Shiu (2012) found out that in the Taiwan stock market, Nison (1991) 2-day reversal patterns do not work, However, they document that patterns 1234 (downwards candle followed by another downwards candle but with open below the previous candle's close) works as a bullish pattern in downtrend markets and 1324 (downwards candle followed by another downwards candle but with open within the previous candle's close) works as a bullish pattern in uptrend markets.

Even more recently, in a study conducted in the Taiwan stock market comprising the period 1992-2009, out of 12 candlestick patterns studied, only three turn out to be profitable after transaction costs, being that those are reversal bullish signals (Lu, 2014). It is also verified that in terms of size, the predictive power of candlesticks increases when analyzing small and low-priced stocks.

In sum, Marshall et al. (2006) extensive and detailed work can be considered to be the seminal work of candlestick charting. Likewise, Goo et al. (2007), introduce features not previously addressed, such as stop-loss levels and the dependence between candle formations and holding periods, which depicts the true complexity of those strategies.

2.3 Chart patterns

Chart patterns are treated as an inconclusive and subjective matter of financial analysis, thus, the practice of identifying them is sometimes considered an art, according to author and financial analyst Justin Kuepper. Like candlestick charting, chart patterns are price formations that tend to repeat over time, very noticeable when observable and easily identifiable by software packages. However, these formations do not generate correct signals all the time, meaning that any individual interested in using them should choose them very carefully. Likewise, in chart patterns, the main formations represent continuation and reversal patterns, which possess different success rates among different instruments and time frames.

The chart patterns theme has been introduced as another trading tool, however, once again, due to its subjectivity of application, it has been barely a subject of thorough analysis, as Lo, Mamaysky, and Wang (2000) point out.

This technique, mostly known as charting analysis, is conducted by analyzing historical prices with the intention of recognizing implied geometric shapes that, depending on the analyst's knowledge and point of view, will lead to buy or sell a certain tradable asset within a particular time frame.

A detailed strategy considered to use a unique approach is applied on a set of large U.S. stocks of NYSE/AMEX and NASDAQ to detect technical patterns using a nonparametric kernel regression, for the period 1962-1996 (Lo et al., 2000). In order to conduct the

experiment, it is devised an algorithm for an automatic detection of chart patterns, being that it is based on the definition of every pattern's geometric shape. The chart patterns' selection was based on its popularity and the ones chosen are head-and-shoulders and inverse head-and-shoulders, broadening tops and bottoms, triangle tops and bottoms, rectangle tops and bottoms and double tops and bottoms. Regarding the algorithm used, authors state that even though it provided sound results, human reasoning and analysis capabilities are still better than algorithms in the digital pattern recognition domain. Based on their main smoothing technique, the nonparametric kernel regression, they concluded that some chart patterns can provide relevant information, especially over long periods of time. However, it does not mean that technical analysis can produce trading profits above the market's benchmark.

With the intent to find out whether technical analysis is a relevant trading tool as technical investors purport it to be, Neftci (1991) delves into the statistical part of the subject. In order to verify that, his study focuses on popular chart patterns, namely the head-and-shoulders and the triangles. The author states that to obtain a head-and-shoulders pattern, the heights of the local minima in the first and third sets must be approximately the same, and the levels of the local minima in the second set must be significantly higher than the first and third sets. Also, he posits that signals generated using observable head-and-shoulders patterns do not correspond to Markov times. After analyzing the consequences derived from the criteria applied in financial markets to study the technical analysis effects, only a few rules generate good enough forecasting techniques.

A research conducted on the S&P 500 and the Russell 2000 indexes, for the period 1990-1999, with the interest to find the predictability of future prices, when using the head-and-shoulders chart pattern, shows no profitability when using the referred technical analysis tool on its own (Savin, Weller and Zvingelis, 2007). It is used a partially modified algorithm based on the work of Lo et al. (2000) with filters based on popular chart patterns retrieved from Thomas Bukowski's book *Encyclopedia of Chart Patterns* (2000). A particularity of this research, is that its foundations depend on the only book related to technical analysis that, at the time, provided a thorough set of statistical analysis with price data that ease the process of investigation. Thanks to technical analysts leading role as market researchers to

find new relevant indicators, the authors, additionally use four different features, particularly, an identified pattern dubbed as “neckline crossing condition”.

As a result, it is found that for both sets of stocks, the head-and-shoulders pattern is able to predict a future decline of prices when it is identified as a bearish reversal pattern according to the charting theory. Furthermore, it is assumed that the pattern’s capabilities derive from the fact of detecting beforehand which stocks are significantly going downwards, i.e., negative momentum stocks. In terms of results, it is shown that risk-adjusted returns would be in the 5-7% range, on a yearly basis.

A former study, conducted on daily spot rates on major currency pairs (Japanese Yen, German Mark, Canadian Dollar, Swiss Franc, French Franc and British Pound) against the U.S. Dollar, for the period 1973-1994, attempts to study the head-and-shoulders predictability of future prices (Chang and Osler, 1995). It is assumed that exchange rates follow a GARCH process instead of a random walk. Some features are introduced into an algorithm to make the trading environment as close to reality as possible, like a stop-loss and a bounce exit possibility in case price crosses from below the neckline. The exit strategy depends on a preset upper limit above the local minimum or on the number of days preset at the beginning. As a result, the authors find that, using the head-and-shoulders pattern, provides a reliable predictive solution for the Mark and Yen on the actual data when compared to artificial data. For the remaining pairs, the profits obtained from actual data are not very different from the ones obtained for the artificial data. Nevertheless, when analyzing all the data, at once, for all currency pairs, the authors obtain economic and statistically significant results, even after transaction costs.

A slight improvement of the application of head-and-shoulders pattern is provided by Chang and Osler (1999), for the same time interval (1973-1994), this time, testing rationality through profitability and efficiency. They find, once again, that the pattern is profitable for the mark and the yen, but not for the remaining currency pairs.

Other sort of tests, within the chart patterns realm, is conducted for the period 1999-2005, using data from the S&P 100 Index, to test the impact of the confirmation bias in price and the reliability of pattern predictions of currency pairs. They also test whether there is any

type of correlation between jump prices in different moments in time (Friesena, Weller and Dunham, 2009). Overall, the model produces three different outcomes for different time intervals. In the short-term, return autocorrelations are negative, in the medium term positive and in the long run turn negative. Regarding the head-and-shoulders pattern and under a set of medium-frequency signals (M-signals), the head-and-shoulders pattern is formed. Its constitution, i.e., the head and shoulders are formed as a consequence of M-signals, but according to the authors "these signals are less informative and occur more frequently than the low-frequency L-signals". They find that sequential jumps in stock prices are positively autocorrelated and that the results are economic and statistically significant, too.

One can conclude that Lo et al. (2000) research set the pace for chart patterns future development, as they dealt with the main formations for an extended period, particularly in the US stock market. These have been applied to support trading strategies and their detailed analyzes on biases, the nature of data and statistical tests provides insightful ideas for further research.

2.4 Price limits (support and resistance) and the clustering effect in the foreign exchange market

Studies regarding currency trading have noticed that around support and resistance areas a set of clusters are formed and as a consequence some repetitive patterns can be identifiable. A research related to orders' clustering around stop-loss and take-profit orders was conducted for a set of three currency pairs, USD/JPY, GBP/USD and EUR/USD, for the period August, 1999 to April, 2000, and the data includes 9655 orders with a total value of 55 billion dollars (Osler, 2003). Authors find that traders' decisions relative to stop-loss and take-profit orders cluster at round numbers. However, depending on the type of order, the results differ slightly. Take-profit orders, contrarily to stop-loss orders, cluster more at round numbers, especially the ones ending in 00. On the other hand, stop-loss levels present different results depending on the order's direction. Stop-loss buy orders cluster more above round numbers whereas stop-loss sell orders cluster more right below round numbers. They bring forth, too, some possible explanations regarding trends' direction once the asset price reaches support and resistance levels. They state that, possibly, take-profit orders are the source of trend reversals

because they usually tend to happen at levels ending in 00. Also, possibly, stop-loss orders are the source of a faster developing trend because it happens when the trend crosses round number levels.

In a previously conducted study, it is shown that the foreign exchange market is not the only market where evidence of price clusters exists (Grossman, Miller, Cone, Fischel and Ross, 1997). It is also present in other highly competitive markets as the NYSE, the AMEX, the London Stock Exchange and the London Bullion Market. According to their findings, one of the reasons for clusters' formations is the fact that investors trade-off higher variability in assets prices for reduced costs. Clusters seem to be formed according to market's structure, volatility of prices and transactions' size. Then, it is inferred that, clustering patterns change depending on the market, assets and period under analysis. Regarding the forex market, they posit that the currency pair JPY/DM (Japanese Yen/Deutsche Mark) produces more exchange rate clusters than USD/JPY or USD/DM. A collusion hypothesis is also addressed as a reason for clustering occurring at the Nasdaq Stock Market. Yet given that this is an electronic-only network and that the sheer number of sellers is so high (400 firms since 1983), it is unlikely that collusion is the base for the occurrence of clusters.

Using technical signals from six unrelated market participants, from 1996 to March, 1998, Osler (2000) propose an analysis of three currency pairs, USD/DM, USD/JPY and GBP/USD, in order to find some relationship between support and resistance levels and future exchange rates change. The author finds that trends were stopped once they reached support and resistance levels more often than not when compared to random levels. Also, she finds that round prices ending with 0 or 5 occur 96% of time and the ones ending with 0 occur 70% of the time. However, she states that both support and resistance levels change depending on the firm and pair chosen.

In a primary auction market, on the Israeli IPO market, there is also evidence that investors are more likely to use round prices, especially the ones ending with 0 or 5, being the former more often present than the latter.

The analysis, performed on the collected data, for the period December, 1993 to February, 1994, by Kandel, Sarig, and Wohl (2001), reveals no specific investors' behavior when orders

are submitted to the issuing firm. Then, it is concluded that clustering depends on the investors' bias to reuse similar end numbers from other similar situations.

To finish up, both works of Osler (2000) and Osler (2003) reach sound findings regarding support and resistance levels, which can provide timely setups for trading currencies.

2.5 Moving Average Convergence Divergence (MACD) technical indicator

2.5.1 MACD's standard application

The MACD indicator is a trend-following and simultaneously a momentum technical analysis tool which is represented as the difference between two exponential moving averages of different lengths. It is computed as the difference between the short-term and the long-term exponential moving averages, usually with a 12-day short-term and 26-day long-term exponential moving averages. As a standard component of the indicator, a signal line is simultaneously used, which normally takes the 9-day exponential moving average of the MACD line. When combined, the set of parameters become represented as [12, 26, 9].

2.5.2 MACD applied to the forex market

Investors have been using technical analysis techniques for a long time, yet empirical evidence is scarce.

A thorough study conducted for the period between January 3, 1989 and December 31, 1996, using two sub-periods, by Papadamou and Tsopoglou (2001) looks for some technical rules' predictive power, namely MACD's predictive power, for USD/DM and USD/GBP currency pairs daily spot exchange rates, when compared to a buy and hold strategy. They also analyze the Moving Average Crossover System (exponential long-term and short-term moving averages) and Momentum. They analyze the risk involved in each transaction as well as the transaction costs incurred when executing orders. Due to the inherent possibility that random results could be produced, the authors use a set of variants for each system. Then, the results are based on 25, 12 and 13 variants of the Moving Average Crossover, Momentum and MACD, respectively. They use as a reference the results from Menkhoff and Schlumberger (1995). The authors show that profitability found is due only to the first sub-period (January 3, 1989 to December 21, 1992) orders as a result of exchanges rates' high volatility. On the

other hand, in the second sub-period, the currency market does not portray a clear market direction, resulting in an increasing number of trades and transaction costs as well. Statistically, the profits obtained with the set of systems are not statistically significant, even though the results show that the systems yield positive returns.

A recent empirical investigation, conducted in the currency market, for the EUR/USD pair, comprising the period 2000-2011, analyzed the MACD [12, 26, 9] technical indicator reliability to predict the referred pair's price direction (Vajda, 2014). In order to account and test for stock market and market macroeconomic episodes, the period was divided in three sub-samples: 2000-2003 (Dot-com bubble), 2004-2007 (ordinary period) and 2008-2011 (Financial Crisis). The indicator was applied on four different time frames: 15 minutes, 30 minutes, 1 hour and 4 hours. In each order execution, a fixed 1 lot is used, and no money management practices are employed, such as stop-loss or take-profits levels, and no transaction costs are taken into account. For the period 2000-2003, the pair is only profitable for the 1-hour time frame, resulting in +1,848 pips with -305 and +1,899 pips of minimum transitory loss and maximum transitory profit, respectively. For the second sub-sample, the pair is only profitable for the 4-hour time frame, resulting in +392 pips with -124 and + 422 pips of minimum transitory loss and maximum transitory profit, respectively. In the last sub-period, the pair is only slightly profitable for the 15 minutes' chart time frame, resulting in +141 pips with an extreme minimum transitory loss of less than -2,500 pips. Regarding the overall results, the only profitable strategy occurs for the 1-hour period resulting in +999.5 pips. On the other hand, an optimization is conducted using fixed levels of 41.5 pips for the stop-loss level and 84.5 pips for the take-profit level. As a result, it is obtained a profit of +2,666.5 pips. So, according to the author, it is possible to use the predictive power of the MACD to profit in the currency exchange market, but investors should employ money management tools due to the market's high volatility levels.

Yazdi and Lashkari (2013) perform a similar study but with a different set of assumptions. The most noticeable assumptions are the take-profit and stop-loss levels set for 30 pips and the fact that the transactions costs are taken into account. The study covers the period 2001-2010 and analyzes four currency pairs (EUR/USD, GBP/USD, USD/JPY and USD/CHF).

Their results show a profit of 182 pips for the EUR/USD pair and losses of 3,314, 4,720 and 1,180 pips for the GBP/USD, USD/CHF and USD/JPY currency pairs, respectively[2]. They concluded that the MACD approach to the EUR/USD provided the better results and considered it to be the most effective.

In sum, even though the work produced by Yazdi and Lashkari (2013) provide a thorough study to date on the MACD application to the foreign exchange market, the evidence is not conclusive of the validity of this tool.

Given that there are only a few studies on the predictability of technical analysis tools, especially in the foreign exchange market, we decide to investigate more this topic providing further evidence on the magnitude and statistical significance of the profits generated by a trading strategy based upon the MACD Divergence.

[2] The pip value is equal to the quantity traded in pips (size in units times pip in decimal places) to the current market price

3 Methodology

In this section, we explain the technical indicator's choice and functioning, and how we apply the method to the foreign exchange market. Then, we describe the variables and the metrics to evaluate the performance of the strategies analyzed.

3.1 Trading strategy implementation

3.1.1 Indicator's selection

From the outset, the indicator's choice, the Moving Average Converge Divergence (MACD), was of prime importance because it may impact the results and the conclusions and, as such produce less or more relevant results for the academia and ultimately, to financial practitioners. Secondly, the choice depended on the indicator's possibility to be approached through different points of view, allowing for the testing of different methods. Also, the indicator's allows changes in its constituents' configurations, i.e., the moving average lengths, allowing more tests and, consequently, more relevant conclusions. Thirdly, the abundance of financial instruments, in which it can be applied, provides an additional option of the research. Furthermore, because it can be applied to any tradable financial instrument, it can be tested using an online platform and hence, it is programmable and changed at will, according to the strategy outlined or any variation.

Another potential advantage of the MACD, is the fact that, given that it has not been analyzed, at least not published in a renowned journal, none of the trading rules are apparently widely known.

Given the nature of our study, we take a quantitative approach, so we can compare the differences in the results produced and simultaneously assess the reliability of each method against the remaining ones, i.e., compare the results of the variants of the MACD indicator over time.

3.1.2 MACD Divergence strategy

Given that the indicator depends on trends to provide non-zero returns, the divergence strategy using the MACD can be used to take advantage of trending markets through inflection points on the asset's price and on the indicator's value, simultaneously. The

divergence strategy compares the price data with the indicator's data to detect when the asset's price movement diverges from the indicator's value movement and vice versa.

According to the underlying theory there are two distinct types of divergence, the classical and the hidden divergences. Both of them occur when the asset's price moves in one direction while the indicator's value moves in the opposite direction.

In terms of order's execution, in the presence of a bullish (bearish) *classical* divergence, the trader buys (sells) when the asset's price reaches a lower low (higher high) and the indicator's value moves in the opposite direction.

In the presence of a bullish (bearish) *hidden* divergence, the trade buys (sells) when the asset's price reaches a higher low (lower high) and the indicator's value moves in the opposite direction.

Divergence is assessed daily or weekly, by the end of the day or week, respectively. After that period, if the indicator detects a divergence, it acts accordingly.

The returns are computed between the asset's closing price and the asset's opening price.
In case two divergences of the same type are identified consecutively, the trader closes the current position and opens another one with the same direction.

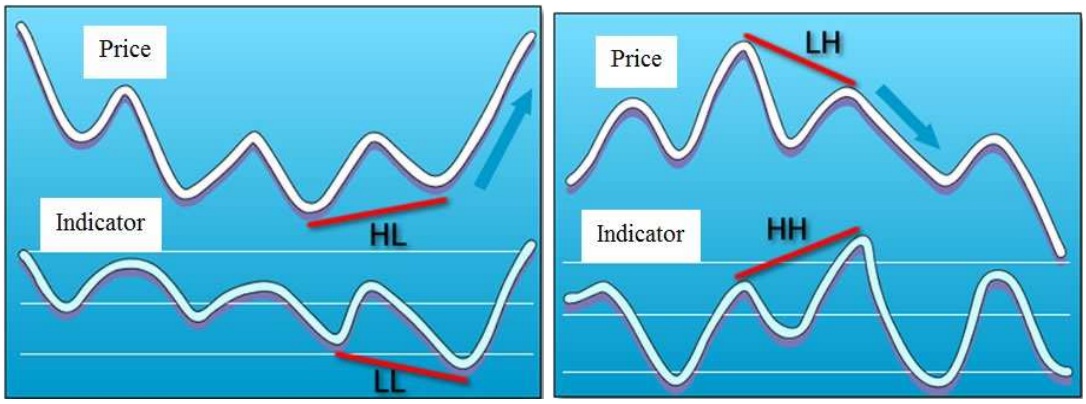
The algorithm repeats the process every time it spots a divergence. Once a position is opened, the algorithm starts searching for new divergences and the process is repeated until the end of the period's range. Every position remains opened until a new signal is generated, which means we always have an open position for the entire period.

The following figures represent the four possibilities of divergence. The upper line represents the price line and the inferior line represents the indicator's line. The upper (lower) arrow represents a buying (selling) order. The LL stands for lower low, HL stands for higher low, HH stands for higher high and LH stands for lower high. The figures below were retrieved from Babypips.com.

Figure 3.1: Bullish and Bearish Classical Divergences (from left to right)



Figure 3.2: Bullish and Bearish Hidden Divergences (from left to right)



Source: Babypips.com

3.1.3 MACD calculation process

The different steps followed to compute the MACD value for each time interval are the following: in the first step we collect the historical closing prices (P) from the outset to the end for each time interval of the time frame chosen; in the second step we compute the EMA_t (exponential moving average), where *t* refers to today and *t*-1 refers to the previous period and the Time Period (*T*) is the number of periods used in the *t*-day EMA, calculated as in equation (3.1). In this equation, for the first interval, the EMA_{t-1} is the trailing *t*-day simple average (for the following periods the EMA_t is given by equation (3.1)). We calculate both short and long-term exponential moving averages for each interval.

$$EMA_t = P_t \frac{2}{T+1} + EMA_{t-1}\left(1 - \frac{2}{T+1}\right) \tag{3.1}$$

$$MACD\ (line) = Short\ term\ EMA - Long\ term\ EMA \quad (3.2)$$

Using equation (3.2), we compute the MACD value, which we use in the algorithm's application of the MACD Divergence strategy.

The most widely used settings are [12, 26, 9], respectively, for the short-term exponential moving average, long-term exponential moving average and signal line (short-term exponential moving average of the MACD line).

3.1.4 Time frames

Historically, when testing technical analysis indicators on raw data, it is verifiable that as the time period used to calculate the indicators increases, the signals generated become stronger and carry a lot more weight into the analysis process rather than in shorter periods. So, we choose to use daily and weekly data.

3.1.5 Selection of parameters

The parameters applied to the currencies are the backbone of the Divergence strategy, i.e., they are the ones who define when the signals are formed. The set of parameters chosen to test were the following: [12, 26, 9], [19, 39, 9], [6, 19, 9] and [15, 33, 5] being the first three derived and applied by the MACD creator (Appel, 2005) to which we add a new one.

3.1.6 Selection of currencies

The process of choosing which currency pairs to test is based on the assumption of Asian and Australasia currencies' pairs longer-lasting trends as a result of being involved in the carry trade practice versus European and American currencies. The fact that all pairs, except for the AUD/USD, are minor currency pairs may produce unexpected results. Moreover, given that they are not included in the majors' category, they can be perceived as low quality type of investments. On the other hand, the lack of correlation among currency pairs, as observable on Appendix III, was taken into account. The pairs chosen to analyze were the AUD/NZD, AUD/USD, CAD/CHF and GBP/JPY.

3.1.7 Transaction costs

Contrarily to the equity market, where brokers charge a commission according to the number of shares bought or by bundle acquired, in the forex market the prevalent cost of trading is charged only through the bid-ask spread between both currencies. The bid-ask spread corresponds to the broker's main income that is paid by traders when opening a position. Also, the bid-ask spread is not a fixed amount, depending mainly on the broker's choice (account type and platform) and on the market conditions at each moment in time. Based on that, we use the historical average floating bid-ask spread for the currency pairs chosen gathered from the platform of one of the major London-based online brokers[3]. The rollover swap rates, which are used to compute the daily swap value for overnight positions were obtained in the same platform. Also, we assume that the strategy is performed in a country where there are no capital gains taxes.

3.1.8 Platform's choice

We use an online trading platform, Metatrader 4, designed especially for forex trading. The tests were carried out based on data gathered in the same platform, comprising 23 years of historical prices. The simulations for each rule's variation were done in Microsoft Excel.

3.1.9 Performance metrics

The set of analyzes is conducted for all the referred currency pairs (4), time frames (2) and sequences of MACD parameters (4) resulting in 32 different situations. In order to make all the results comparable across the different strategies' variations, we select a set of metrics. The performance metrics chosen are: gain and loss; positions; position properties; win/loss series; drawdown; indexes; and expenses.

Regarding *gain and loss*, we use simple gross and net returns and standard and Islamic portfolio net returns. In the *positions category*, we use the total number of positions and profitability of higher high and lower low positions, and profitable and losing positions (percentage) including both the classic and the hidden divergences' positions. The *position*

[3] FxPro Metatrader 4. See Appendix V for details.

properties category includes the reward/risk ratio as the ratio between average profitable and losing trades (in money terms) and the largest profitable and losing trades. The *win/loss series* contains maximum consecutive profit and loss (drawdown) and the balance drawdown (percentage), which is the largest drop of the account balance below the initial balance value. The *indexes* category includes the ex-post Sharpe ratio given by the ratio between the realized return and the standard deviation and the recovery factor, expressed by the ratio between net profit and the drawdown value (in money terms). The *expenses* category, which includes the bid-ask spread and the swaps, are embedded in the net returns computed in the gain and loss category.

Additionally, we perform statistical inference tests using the Student's t-test and the Welch's t-test to assess if the returns for the top performing system based on the recovery factor are statistically different to the ones of the bottom performing system, based on the recovery factor, for both daily and weekly time frames.

4 Results

In this section, we analyze 32 systems, compiled using the R programming language on RStudio and processed on Excel. The analyzes are:

(1.): computation of a set of scoring metrics for the totality of the 32 systems;

(2.) illustration of the best portfolio strategy across currency pairs and time frames based on the recovery factor metric;

(3.) comparison of best portfolio net return (%) system based on the recovery factor metric with a yearly carry trade portfolio strategy based on the same currency pair;

(4.) anomalies' testing, for the daily time frame, dependent on the identification of the best portfolio net return (%) system based on the recovery factor metric;

(5.) computation of the best yearly portfolio net return (%) based on the recovery factor metric for the period 1994-2016.

To implement the strategy, we had to allow for some simplifications due to lack of data or inability to get it. We mention these in the following sections.

4.1 Constraints

4.1.1 Bid-ask spread

As a simplification, for all the equations below, we use the closing price in the place of the ask price. Nonetheless, the bid-ask spread (points) use the actual ask price because it was obtained directly from the platform. We use equations (4.1) and (4.2) to calculate the bid-ask spread in points for pairs with four and two decimal places, respectively. As stated on equation (4.3), we use it to obtain the bid-ask spread as margin. Lastly, equations (4.4) and (4.5) provide us with the bid-ask spread in currency value per lot for long and short positions, respectively.

$$Bid - ask\ spread\ (BA)\ (points) = BA\ spread\ (pips) * 0.0001 \quad (4.1)$$

$$BA\ spread\ (points) = BA\ spread\ (pips) * 0.01 \quad (4.2)$$

$$BA\ spread\ (margin) = \frac{BA\ spread\ (points)}{Ask} \tag{4.3}$$

$$BA\ spread\ (long) = Lots\ (currency) * BA\ spread\ margin \tag{4.4}$$

$$BA\ spread\ (short) = Lots\ (currency) * BA\ spread\ margin \tag{4.5}$$

Exception to the rule, the pip value is fixed and equal to $10 for a standard lot, when the US dollar is listed as the counter currency and the trading account uses the US dollar as the deposit currency.

The following table provides the bid-ask spreads used to calculate the brokerage house margin.

Table 4.1: Bid-Ask spread

This table displays the average markets' floating bid-ask spread in pips for the following currency pairs: Australian Dollar/New Zealand Dollar, Australian Dollar/US Dollar, Canadian Dollar/Swiss Franc and British Pound/Japanese Yen.

Pair	AUDNZD	AUD/USD	CAD/CHF	GBP/JPY
Bid-Ask spread (pips)	4.5	1.4	3.7	3.0

The bid-ask spread is a one-time operation per period, taken into account before each order is executed, corresponding to the operational cost of trading.

4.1.2 Swap value

Even though we have access to the historical overnight lending rates of the countries used in our analysis, the historical swap values provided to clients by FxPro and other forex brokers are not freely available. Due to the lack of data, we use the swap values provided by FxPro for the week 13 March, 2017– 17 March, 2017, as shown in Table 4.2.

Table 4.2: Swap rates for currency pairs by broker and position type

This table lists the swap rates provided by brokers Forex4You, FxPro and OctaFX for both short and long positions when trading the following currency pairs: Australian Dollar/New Zealand Dollar, Australian Dollar/US Dollar, Canadian Dollar/Swiss Franc and British Pound/Japanese Yen.

Position type	Swap rate short position			Swap rate long position		
Pair/Broker	Forex4You	FxPro	OctaFX	Forex4You	FxPro	OctaFX
AUD/NZD	0.02	-2.72	-17.20	-0.43	-4.84	-3.90
AUD/USD	-0,77	-2.99	-19.00	0.10	0.38	5.80
CAD/CHF	-0.75	-4.79	-4,.60	0.09	-0.10	-0.10
GBP/JPY	-0.49	-3.51	-4.30	0.04	-2.73	-0.10

Given the data gathered for several brokers, we decided to choose FxPro as the reference, since it is a long-standing and solid broker, and offers the range of swaps one would face with a broker with the same level of market recognition and clients' execution, support and protection.

In order to calculate the swap value in currency per lot we use equation (4.6).

$$Swap\ value = \frac{Pip\ value * Swap\ rate * Number\ of\ days}{10} \tag{4.6}$$

For each period, we take the swap value as a single operation, i.e., as the sum of each daily swap value. For simplification purposes, we do not take into account the time value of money.

4.2 Performance metrics for the 32 MACD Divergence system variations

The scoring metrics analyzed downwards and the data presented in the tables below were computed for the period 1994-2016 using a portfolio strategy, unless stated otherwise. The portfolio strategy entails opening a position with the account's balance total amount.

According to the Table 4.3, for the daily time frame, the AUD/NZD and GPB/JPY pairs are the only ones providing positive returns, even though for a very reduced time span. On the other hand, for the weekly time frame, every pair produces positive returns for at least one set of parameters. In overall terms, based on that this preliminary data, we can state that using the longer time frame and weekly data, an investor has a higher chance of obtaining positive returns in the long-term.

Table 4.3: MACD Divergence: Gain and loss metrics

This table documents, for AUD/NZD, AUD/USD, CAD/CHF and GBP/JPY currency pairs, the portfolio net returns for the period 1994-2016 (daily and weekly data). All the values presented are

expressed in percentage points. Each category uses the following MACD parameters to arrive to the final computation: [12,26]; [19,39]; [6,19]; and [15,33].

Pair	Parameters	Portfolio Net Return (%) Daily Data	Portfolio Net return (%)Weekly Data
AUD/NZD	**[12,26]**	21.75	(17.17)
	[19,39]	31.59	(13.01)
	[6,19]	(28.02)	10.98
	[15,33]	(21.60)	(33.20)
AUD/USD	**[12,26]**	(36.72)	25.31
	[19,39]	(7.63)	72.83
	[6,19]	(27.58)	(45.08)
	[15,33]	(35.15)	32.10
CAD/CHF	**[12,26]**	(32.04)	27.97
	[19,39]	(13.10)	(17.17)
	[6,19]	(25.41)	(30.23)
	[15,33]	(25.53)	(13.96)
GBP/JPY	**[12,26]**	(22.50)	(53.90)
	[19,39]	46.16	9.12
	[6,19]	(33.40)	(42.74)
	[15,33]	(54.74)	(22.43)

4.3 MACD Divergence best system per currency

We study, for each currency pair, across both time frames, daily and weekly, the best set of parameters based on the highest value of the recovery factor. This approach is taken in order to render the results of the analyzes comparable and consequently draw general conclusions.

Concluding all the results using the recovery factor metric, we can identify the optimal set of parameters across currencies and time. Nonetheless, we need to take into account that, from previous tables, namely Table 4.3, we already know that the majority of the sets of parameters could not provide a positive net portfolio return.

The [19,39] set generates the highest and positive returns for the portfolio, with the exception of the weekly-interval returns for AUD/NZD and CAD/CHF pairs, as shown in Table 4.4.

The GBP/JPY pair is the most profitable of all, with the second best risk-adjusted return, higher than 1, and the second best recovery factor, for the daily interval.

Across all pairs, except for the GBP/JPY Weekly and AUD/USD Weekly, the drawdown happened to be higher than the end of period portfolio net return, which means it is difficult to recover from losses as suggested by the recovery factor's figures.

Table 4.4: MACD Divergence: Best system based on recovery factor

This table shows, for all currencies, AUD/NZD; AUD/USD; CAD/CHF and GBP/JPY, the reward/risk ratio; the drawdown in percentage points; the ex-post Sharpe ratio and the recovery factor.

Pair	AUD/NZD	AUD/USD	CAD/CHF	GBP/JPY
Daily				
	[19,39]	**[19,39]**	**[19,39]**	**[19,39]**
Portfolio Net return (%)	31.59	(7.63)	(13.10)	46.16
Reward/risk ratio	1.66	1.16	1.37	1.12
Drawdown (%)	35.56	37.97	40.67	36.07
Ex-post Sharpe ratio	10.39	(1.36)	(3.00)	7.35
Recovery factor	0.76	(0.14)	(0.23)	0.56
Weekly				
	[6,19]	**[19,39]**	**[12,26]**	**[19,39]**
Portfolio Net return (%)	10.98	72.83	27.97	9.12
Reward/risk ratio	0.68	1.16	1.00	2.50
Drawdown (%)	19.58	26.22	36.98	35.08
Ex-post Sharpe ratio	2.56	4.45	3.26	0.63
Recovery factor	0.45	1.19	0.41	0.26

With regard to weekly data, we observe that the [19,39] set now only backs the AUD/USD and GBP/JPY pairs. The AUD/USD pair generates the highest portfolio net return with the second highest risk-adjusted return and the strongest to recover from price troughs. The best positioned currency pair is the GBP/JPY, which was previously ranked as the worst on the daily time frame in terms of risk-adjusted returns. On the other hand, the AUD/NZD presents the lowest drawdown level, which pairs with a positive portfolio net return.

Overall, in terms of efficiency and stability, the best performing pairs are the AUD/NZD Daily and the AUD/USD Weekly, as shown by the ex-post Sharpe ratio. The [19,39] set dominates the profit potential to loss potential (reward/risk ratio) across all pairs, so it should be the primary choice for an investment strategy with lower risk and a higher easiness to recover from transitory losses.

4.4 Active strategy versus Passive strategy

In order to assess how the MACD strategy fares against other market trend-following strategies, we compare with a yearly carry trade strategy (CT). This is a widely used strategy by traders and investors worldwide.

The simulated carry trade strategy was computed as usual, i.e., borrow the low-yielding currency and buy the high-yielding currency. In practice, we go long (short) in a currency pair if the base currency is the high (low)-yielding currency. The strategy is computed using a portfolio, the same as implemented by us using the MACD Divergence Strategy and with the same cost/swap structure.

Then, we compare our best individual currency strategy based on the highest value of the recovery factor with the yearly carry trade strategy.

4.4.1 MACD Divergence strategy versus Carry Trade strategy

According to Table 4.5, the divergence strategy is inferior than the carry trade strategy in terms of net returns, for both the daily and weekly time frames, except for the AUD/NZD pair. Nonetheless, it provides positive risk-adjusted returns and an ability to recover from losses, similar to what occurs in the carry trade strategy.

Table 4.5: MACD Divergence versus Carry Trade

This table summarizes a set of measures to assess how the MACD Divergence Strategy performs against the Carry Trade Strategy (CT).

Panel A			
Pair	AUD/NZD Daily	AUD/NZD Weekly	CT AUD/NZD

	[19,39]	**[6,19]**	
Portfolio Net return (%)	31.59	10.98	(10.34)
Reward/risk ratio	1.66	0.68	0.88
Drawdown (%)	35.56	19.58	24.42
Ex-post Sharpe ratio	10.39	2.56	(1.87)
Recovery factor	0.76	0.45	(0.63)

Panel B

Pair	AUD/USD Daily	AUD/USD Weekly	CT AUD/USD
	[19,39]	**[19,39]**	
Portfolio Net return (%)	(7.63)	72.83	108.84
Reward/risk ratio	1.16	1.16	1.14
Drawdown (%)	37.97	26.22	24.51
Ex-post Sharpe ratio	(1.36)	4.45	8.21
Recovery factor	(0.14)	1.19	1.61

Panel C

Pair	CAD/CHF Daily	CAD/CHF Weekly	CT CAD/CHF
	[19,39]	**[12,26]**	
Portfolio Net return (%)	(13.10)	27.97	35.92
Reward/risk ratio	1.37	1.00	0.71
Drawdown (%)	40.67	36.98	28.07
Ex-post Sharpe ratio	(3.00)	3.26	3.52
Recovery factor	(0.23)	0.41	0.74

Panel D

Pair	GBP/JPY Daily	GBP/JPY Weekly	CT GBP/JPY
	[19,39]	**[19,39]**	
Portfolio Net return (%)	46.16	9.12	75.25
Reward/risk ratio	1.12	2.50	0.76
Drawdown (%)	36.07	35.08	42.41
Ex-post Sharpe ratio	7.35	0.63	5.78
Recovery factor	0.56	0.26	0.71

The MACD Divergence strategy provides better risk-adjusted returns than the carry trade for all pairs, except the AUD/NZD Weekly. However, the MACD Divergence strategy provides only a higher stability than the carry trade for the AUD/NZD and GBP/JPY Daily.

Regarding the recovery factor, for the AUD/USD, CAD/CHF and GBP/JPY, the carry trade provided a slightly better chance of recouping from provisional losses.

Overall, we can affirm that the MACD Divergence is a superior strategy in terms of lowering the riskiness involved whereas the carry trade is better in terms of net returns and stability of returns, except for the AUD/NZD pair.

4.5 Statistical tests based on the recovery factor

4.5.1 Best MACD Divergence versus worst MACD Divergence systems

In this section, we analyze the statistical significance between returns for two different sets of data. We compare the returns of the best system based on the recovery factor with the worst system based on the recovery factor. Depending on the features of the data we use a parametric or non-parametric test.

Based on information provided in Table 4.6, we can easily identify the recovery factor's best and worst systems for both time frames. Then, we can proceed with the identification and testing of assumptions of the standard test for two sets of data, the Student's t-test, in order to opt for the most reliable and closest type of distribution test for our data.

Table 4.6: MACD Divergence recovery factor's best and worst systems

This table summarizes the recovery factor's best (✓) and worst (x) system per currency pair based on parameters for both daily and weekly intervals.

Pair	AUD/NZD		AUD/USD		CAD/CHF		GBP/JPY	
				Daily				
Parameters	Best	Worst	Best	Worst	Best	Worst	Best	Worst
[12,26]				x				
[19,39]	✓		✓		✓		✓	
[6,19]		x						

[15,33]						x		x
				Weekly				
[12,26]					✓			
[19,39]			✓				✓	
[6,19]	✓			x		x		x
[15,33]		x						

4.5.1.1 Detailed tests

4.5.1.1.1 Test for normality distribution

In order to assess the normality of data, given it is a prerequisite when conducting parametric tests, we use the Shapiro-Wilk Normality Test. The Shapiro-Wilk Test's null hypothesis states that the sample data is normally distributed. Given a significance (alpha) level of 0.05, we reject the null hypothesis when the *p*-value is lower than the alpha level, meaning there is evidence that the data do not follow a normal distribution.

The results in Table 4.7, suggest that returns do not follow a standard normal distribution.

Table 4.7: Statistical significance of Shapiro-Wilk Normality test

This table illustrates, for a 95 % confidence level, the *p*-value across the different currency pairs for both the recovery factor's best and worst system based on parameters, when testing for the data's normality. The distribution type can be normal (N) or non-normal (NN).

Pair	AUD/NZD		AUD/USD		CAD/CHF		GBP/JPY	
				Daily				
Category	Best	Worst	Best	Worst	Best	Worst	Best	Worst
Parameters	**[19,39]**	**[6,19]**	**[19,39]**	**[12,26]**	**[19,39]**	**[15,33]**	**[19,39]**	**[15,33]**
p-value	0.000	0.099	0.043	0.043	0.904	0.557	0.002	0.143
Distribution type	NN	N	NN	NN	N	N	NN	N
				Weekly				
Parameters	**[6,19]**	**[15,33]**	**[19,39]**	**[6,19]**	**[12,26]**	**[6,19]**	**[19,39]**	**[6,19]**
p-value	0.555	0.356	0.028	0.462	0.406	0.450	0.005	0.125

Distribution type	N	N	NN	N	N	N	NN	N

4.5.1.1.2 Test for variances' heteroscedasticity

We also performed the Levene's test for the same data, where the null hypothesis states that the samples' data variances are equal. Given a significance (alpha) level of 0.05, we reject the null hypothesis when the *p*-value is lower than the alpha level, meaning that variances are different across the selected samples.

On the other hand, we have to stress that this test, often has a low statistical power and therefore it fails to reject the null hypothesis that variances are equal. Consequently, it leads to the occurrence of the type II error. Nonetheless, we present the statistical significance of the Levene's test across currency pairs for both daily and weekly intervals, in Table 4.8. Overall, based on the *p*-values we cannot expect that the variances across samples and time frames are the same.

Table 4.8: Statistical significance of Levene's test

This table documents the *p*-value across the different currency pairs for the recovery factor's best and worst system sets based on parameters, when testing for the data's homogeneity of variances.

Pair	AUD/NZD		AUD/USD		CAD/CHF		GBP/JPY	
Daily								
Category	Best	Worst	Best	Worst	Best	Worst	Best	Worst
Parameters	**[19,39]**	**[6,19]**	**[19,39]**	**[12,26]**	**[19,39]**	**[15,33]**	**[19,39]**	**[15,33]**
p-value	0.044		0.313		0.838		0.645	
Weekly								
Parameters	**[6,19]**	**[15,33]**	**[19,39]**	**[6,19]**	**[12,26]**	**[6,19]**	**[19,39]**	**[6,19]**
p-value	0.663		0.003		0.189		0.068	

4.5.1.2 Welch's t-test

Given that the Student's t-test assumptions do not hold; we assume that the Welch's t-test is a better alternative to proceed with the inferences in our data given its broad applicability to

non-normal data. Besides that, the Welch's t-test is robust for skewed distributions and large sample sizes.

The Welch's t-test null hypothesis is that the two populations have equal means. Given a significance (alpha) level of 0.05, according to Table 4.9, we cannot reject the null hypotheses in any case, due to *p*-values higher than 0.05, meaning that the recovery factor's best and worst system sets based on parameters do not have statistically significant different means.

Table 4.9: Statistical significance of Welch's t-test

This table shows the difference between the *p*-value across the different currency pairs for the recovery factor's best and worst system sets.

Pair	AUD/NZD		AUD/USD		CAD/CHF		GBP/JPY	
Daily								
Category	Best	Worst	Best	Worst	Best	Worst	Best	Worst
Parameters	**[19,39]**	**[6,19[**	**[19,39]**	**[12,26]**	**[19,39]**	**[15,33]**	**[19,39]**	**[15,33]**
Sample size	124	209	121	165	123	135	103	119
p-value	0.227		0.644		0.838		0.201	
Weekly								
Parameters	**[6,19]**	**[15,33]**	**[19,39]**	**[6,19]**	**[12,26]**	**[6,19]**	**[19,39]**	**[6,19]**
Sample size	38	26	20	44	31	40	23	46
p-value	0.160		0.233		0.341		0.567	

4.5.2 Best MACD Divergence based on the recovery factor versus best Carry Trade strategy

As an additional statistical test, we proceed with the verification of the statistical significance between the means of the populations of the best system based on the recovery factor and the carry trade strategy across parameters and time frames.

According to the prior procedural tests, we verified that the Welch's t-test was the best fit to test the data, including the data applicable to the best system based on the recovery factor, so, we use it again for this analysis.

According to Table 4.10, we do not reject the null hypotheses for any case, due to *p*-values higher than 0.05, meaning that the recovery factor's best and carry trade sets based on parameters do not have statistically significant different means.

Table 4.10: Statistical significance of Welch's t-test

This table documents the *p*-value across the different currency pairs for the recovery factor's best and Carry Trade (CT) sets based on parameters, when testing for the hypothesis that the two populations for each currency pair have equal means.

Pair	AUD/NZD		AUD/USD		CAD/CHF		GBP/JPY	
Daily								
Category	Best	CT	Best	CT	Best	CT	Best	CT
Parameters	**[19,39]**		**[19,39]**		**[19,39]**		**[19,39]**	
p-value	0.633		0.180		0.406		0.337	
Weekly								
Parameters	**[6,19]**		**[19,39]**		**[12,26]**		**[19,39]**	
p-value	0.620		0.982		0.798		0.804	

4.5.3 Discussion of main results

Firstly, our attempt to provide an alternative, active type of investment to the masses was quite unfruitful, because the MACD Divergence does not consistently provide positive returns. Moreover, it does not provide higher net returns than the carry trade strategy. However, it is superior to the carry trade strategy when assessing strategies through the risk/reward ratio, taken as a measure of risk-adjusted returns.

Out of the sixteen daily MACD Divergence cases, only three cases are profitable, being two of them of the AUD/NZD pair and the remaining from the GBP/JPY pair. For the longer time frame, the weekly interval-based trading, there are six instances of profitability. Each pair has one profitable set of parameters, except for the AUD/USD pair which displays three cases of profitability for the following sets of parameters: [12,26], [19,39] and [15,33].

When we refer to the best system based on the recovery factor, for the weekly time frame, all the returns are positive. The data shows the highest and lowest net returns of 72.83% and 9.12% for the AUD/USD and GBP/JPY pairs, respectively, with the corresponding [19,39] set of parameters for both instances. In total, the [19,39] set accounts for all the daily sets of the best systems based on the recovery factor and for half on the weekly interval.

Statistically speaking, for both instances, when comparing the best and worst systems based on the recovery factor and when comparing the best system based on the recovery factor with the carry trade strategy, we find that there is no statistically significant (95% confidence level) evidence of different means, meaning that we cannot assert that the results were not randomly obtained.

In appendix, we provide additional results of the MACD Divergence, especially of strategy variations in terms of type of account and type of investment. We highlight the following: the fixed investment strategy and the Islamic-account portfolio results are quite different between themselves and to the MACD Divergence. Also, both the fixed investment strategy and the portfolio investment strategy are unprofitable. The Islamic-account portfolio presents much higher net returns than both of the aforementioned strategies because it does not take into account the swap values, which were quite costly according to Table 4.2.

Regarding the positions' category (Appendix I.2), even though not stated in any table, due to the specific development of the MACD Divergence, there are almost no signals from hidden divergences. This means that our strategy concept is based uniquely on classical divergences.

5 Conclusions

The purpose of this work was to evaluate the predictability of the MACD Divergence strategy over the period from 1994 to 2016, and to compare its results with a benchmark trading strategy in the foreign exchange market, the carry trade.

When we started this work, there was no published work of the MACD Divergence strategy. The most closely related work come from Vajda (2014) and Yazdi and Lashkari (2013) which use variations of the MACD Crossing strategy.

We devised an algorithm to identify the divergences between the asset's price and the indicator's value, choosing the currency pairs and defining the time frames. We also simulated the carry trade for the same set of pairs and time frames and ultimately proceeded with the statistical analysis. For the sake of simplicity, we have used no stop-loss or take-profits levels.

After concluding the work, we realized that we managed to get a simple, yet coherent manual trading system. It can be fully automated for live trading and allow future researchers to have a new glimpse into a technical analysis indicator's features and performance.

Overall, the results suggest that the [19,39] set is the most consistent and stable rule to follow when trading the AUD/NZD and GBP/JPY pairs, because it provides positive net returns. On the other hand, the carry trade strategy provides substantial positive net returns for the AUD/USD, CAD/CHF and GBP/JPY pairs, not matched by the MACD Divergence strategy.

The main limitations present in this dissertation are the data availability, namely the price data, the bid-ask spread, the swap value and the slippage value. Given their potential to alter the final results of the examined strategies, either upwards or downwards, one should bear in mind that the results we reach represent an approximation of the true performance.

In terms of future research, we propose testing the use of fixed or dynamic stop-loss and take-profit levels and using other (technical) indicators and candlestick charting in order to optimize the MACD Divergence strategy in the foreign exchange market.

6 Appendices

Appendix I - Scoring metrics

I.1 Gain and loss metrics

This table shows, for currency pairs, the simple gross returns, the simple net returns, the portfolio net returns and the Islamic net returns using daily and weekly data. All the values presented are expressed in percentage points. Each category uses the following MACD parameters to arrive to the final computation: [12,26]; [19,39]; [6,19]; and [15,33]. The simple returns use a 100,000 fixed investment (whether the balance is 100,000 or below).

Panel A								
Pair	AUD/NZD				AUD/USD			
Daily								
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**	**[12,26]**	**[19,39]**	**[6,19]**	**[15,33]**
Simple gross return (%)	61.68	66.26	15.77	26.06	(8.87)	28.51	6.41	(15.27)
Simple Net return (%)	26.31	32.29	(20.14)	(8.02)	(28.00)	9.50	(13.29)	(24.54)
Portfolio Net return (%)	21.75	31.59	(28.02)	(21.60)	(36.72)	(7.63)	(27.58)	(35.15)
Islamic Portfolio Net return (%)	84.05	91.47	18.42	28.44	(18.87)	11.83	(4.74)	(26.53)
Weekly								
Simple gross return (%)	13.28	15.32	40.53	(5.07)	49.27	87.17	(15.26)	52.61
Simple Net return (%)	(13,46)	(11.61)	12.19	(31.01)	35.83	79.35	(33.23)	38.44
Portfolio Net return (%)	(17.17)	(13.01)	10.98	(33.20)	25.31	72.83	(45.08)	32.10
Islamic Portfolio Net return (%)	11.05	14.86	46.44	(7.28)	41.59	87.02	(27.82)	45.27
Panel B								
Pair	CAD/CHF				GBP/JPY			
Daily								

	[12,26]	[19,39]	[6,19]	[15,33]	[12,26]	[19,39]	[6,19]	[15,33]
Simple gross return (%)	9.33	2.99	18.31	12.52	18.32	69.30	3.12	(33.70)
Simple Net return (%)	(16.91)	(2.57)	(9.32)	(11.61)	0.98	51.04	(15.27)	(50.47)
Portfolio Net return (%)	(32.04)	(13.10)	(25.41)	(25.53)	(22.50)	46.16	(33.40)	(54.74)
Islamic Portfolio Net return (%)	1.87	(4.02)	13.21	(5.70)	0.56	66.68	(11.71)	(40.76)
Weekly								
Simple gross return (%)	48.11	6.59	(6.92)	14.84	(27.75)	48.62	(9,87)	18.99
Simple Net return (%)	31.34	(9.53)	(22.75)	(3.71)	(42.68)	34.64	(25.05)	4.90
Portfolio Net return (%)	27.97	(17.17)	(30.23)	(13.96)	(53.90)	9.12	(42.74)	(22.43)
Islamic Portfolio Net return (%)	46.13	(3.70)	(13.48)	1.15	(43.65)	29.78	(29.66)	(4.39)

I.2 Positions' category

This table shows the number of higher high (HH) and lower low (LL) positions, the profitability of HH and LL positions in percentage points and the overall profitability for higher high, lower low, higher low (HL) and lower high (LH) positions in percentage points.

Panel A								
Pair	AUD/NZD				AUD/USD			
Daily								
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**	**[12,26]**	**[19,39]**	**[6,19]**	**[15,33]**
# Higher high positions	60	54	93	54	90	67	127	80
# Lower low positions	88	71	117	80	76	55	113	62
HH profitable (%)	63.33	48.15	53.76	55.56	45.56	50.75	48.82	45
LL profitable (%)	40.91	43.66	41.03	42.50	50.00	43.64	51.33	43.55
Profitable positions (%)	47.65	42.74	44.02	45.11	47.27	45.45	47.28	43.97
Losing positions (%)	52.35	57.26	55.98	54.89	52.73	54.55	52.72	56.03
Weekly								

# Higher high positions	11	6	16	11	14	11	28	11
# Lower low positions	17	14	23	16	16	10	17	11
HH profitable (%)	63.64	66.67	68.75	54.55	50.00	54.55	39.29	45.45
LL profitable (%)	41.18	57.14	56.52	25.00	50.00	40.00	47.06	45.45
Profitable positions (%)	48.15	42.11	63.16	30.77	51.72	50.00	38.64	47.62
Losing positions (%)	51.85	57.89	36.84	69.23	48.28	50.00	61.36	52.38
Panel B								
Pair	CAD/CHF				GBP/JPY			
Daily								
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**	**[12,26]**	**[19,39]**	**[6,19]**	**[15,33]**
# Higher high positions	74	55	103	63	75	61	112	65
# Lower low positions	78	69	105	73	59	43	89	55
HH profitable (%)	48.65	43.64	45.63	44.44	38.67	45.90	43.75	41.54
LL profitable (%)	44.87	34.78	48.57	42.47	50.85	55.81	49.44	47.27
Profitable positions (%)	45.03	40.65	43.48	42.96	42.11	50.49	44.50	43.70
Losing positions (%)	54.97	59.35	56.52	57.04	57.89	49.51	55.50	56.30
Weekly								
# Higher high positions	14	10	21	14	18	12	26	15
# Lower low positions	18	12	20	14	12	11	21	10
HH profitable (%)	57.14	50.00	42.86	50.00	22.22	33.33	46.15	26.67
LL profitable (%)	55.56	33.33	40.00	50.00	33.33	27.27	52.38	30.00
Profitable positions (%)	54.84	42.86	42.50	48.15	27.59	30.43	50.00	29.17
Losing positions (%)	45.16	57.14	57.50	51.85	72.41	69.57	50.00	70.83

I.3 Position properties

This table sums up the profitableness metrics of the currency pairs, namely the reward/risk ratio, and the largest single profit and loss.

Panel A				
AUD/NZD				
Daily				
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**

Reward/risk ratio	1.26	1.66	1.08	1.01
Largest single profit	8591.67	9893.22	4823.20	6071.39
Largest single loss	(10705.78)	(6040.03)	(7709.99)	(7346.66)
Weekly				
Reward/risk ratio	0.76	0.90	0.68	0.99
Largest single profit	9393.47	6503.60	8774.55	9909.16
Largest single loss	(11566.61)	(13548.80)	(13388.89)	(10098.42)
Panel B				
AUD/USD				
Daily				
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**
Reward/risk ratio	0.94	1.16	1.00	1.09
Largest single profit	9641.54	25928.36	10892.51	17760.85
Largest single loss	(21431.64)	(44402.00)	(23028.52)	(16256.69)
Weekly				
Reward/risk ratio	1.14	1.46	1.04	1.38
Largest single profit	42221.92	63238.40	14248.34	61122.49
Largest single loss	(19037.88)	(32249.42)	(15627.58)	(26694.89)
Panel C				
CAD/CHF				
Daily				
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**
Reward/risk ratio	1.03	1.37	1.17	1.15
Largest single profit	11700.36	11765.55	8551.78	8529.60
Largest single loss	(11395.32)	(14433.58)	(10468.63)	(12302.84)
Weekly				
Reward/risk ratio	1.00	1.10	0.95	0.96
Largest single profit	27496.07	28104.07	9954.57	32400.01
Largest single loss	(27397.44)	(25169.39)	(13084.09)	(27651.55)
Panel D				

GBP/JPY				
Daily				
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**
Reward/risk ratio	1.21	1.12	1.09	0.94
Largest single profit	17524.52	44897.40	11773.94	13521.17
Largest single loss	(14206.07)	(38761.02)	(16857.42)	(18205.92)
Weekly				
Reward/risk ratio	1.67	2.50	0.73	1.88
Largest single profit	24318.24	26667.52	14815.20	18975.72
Largest single loss	(32021.87)	(26423.36)	(27938.64)	(28002.63)

I.4 Win/Loss Series and Drawdown Class

This table shows the winning/losing streaks (longest consecutive gain/loss): maximum consecutive profit, maximum consecutive loss and balance drawdown.

Panel A				
AUD/NZD				
Daily				
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**
Maximum consecutive profit	59352.73	65070.45	21039.59	35794.68
Maximum consecutive loss	(33032.78)	(41715.09)	(32651.33)	(42267.90)
Drawdown (%)	31.46	35.56	32.05	42.27
Weekly				
Maximum consecutive profit	22122.59	19969.76	32895.81	17817.24
Maximum consecutive loss	(23863.72)	(24560.36)	(24338.85)	(33202.79)
Drawdown (%)	22.38	22.02	19.58	33.20
Panel B				
AUD/USD				
Daily				
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**
Maximum consecutive profit	36807.85	55117.28	49955.64	55637.49

Maximum consecutive loss	(56917.81)	(56530.24)	(62726.80)	(80620.32)
Drawdown (%)	49.57	37.97	51.89	57.37
Weekly				
Maximum consecutive profit	59430.26	134259.89	29984.96	112433.34
Maximum consecutive loss	(58638.98)	(61432.32)	(60045.63)	(89038.40)
Drawdown (%)	37.97	26.22	57.13	41.91
Panel C				
CAD/CHF				
Daily				
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**
Maximum consecutive profit	31061.59	48334.32	46541.96	31298.29
Maximum consecutive loss	(58189.89)	(56105.23)	(43706.24)	(36348.91)
Drawdown (%)	50.54	40.67	42.26	36.18
Weekly				
Maximum consecutive profit	86314.35	40827.06	20580.68	52480.59
Maximum consecutive loss	(67782.80)	(60613.21)	(36461.84)	(65777.59)
Drawdown (%)	36.98	43.04	36.46	44.51
Panel D				
GBP/JPY				
Daily				
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**
Maximum consecutive profit	34705.73	131084.08	27721.00	32328.95
Maximum consecutive loss	(46341.78)	(82470.14)	(86508.07)	(58127.30)
Drawdown (%)	46.21	36.07	67.85	58.13
Weekly				
Maximum consecutive profit	34907.37	44195.95	32257.93	20269.32
Maximum consecutive loss	(74489.54)	(30579.06)	(45938.48)	(42695.24)
Drawdown (%)	61.77	35.08	44.52	42.70

I.5 Indexes

This table shows the ex-post Sharpe ratio and the recovery factor.

Panel A								
Pair	AUD/NZD				AUD/USD			
Daily								
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**	**[12,26]**	**[19,39]**	**[6,19]**	**[15,33]**
Ex-post Sharpe ratio	7.67	10.39	(11.22)	(7.29)	(8.69)	(1.36)	(7.70)	(6.89)
Recovery factor	0.66	0.76	(0.86)	(0.51)	(0.65)	(0.14)	(0.44)	(0.44)
Weekly								
Ex-post Sharpe ratio	(3.34)	(2.90)	2.56	(6.49)	2.40	4.45	(4.88)	2.55
Recovery factor	(0.72)	(0.53)	0.45	(1.00)	0.43	1.19	(0.75)	0.36
Panel B								
Pair	CAD/CHF				GBP/JPY			
Daily								
	[12,26]	**[19,39]**	**[6,19]**	**[15,33]**	**[12,26]**	**[19,39]**	**[6,19]**	**[15,33]**
Ex-post Sharpe ratio	(7.69)	(3.00)	(7.02)	(6.07)	(4.02)	7.35	(7.72)	(9.42)
Recovery factor	(0.55)	(0.23)	(0.58)	(0.70)	(0.49)	0.56	(0.39)	(0.94)
Weekly								
Ex-post Sharpe ratio	3.26	(1.67)	(4.50)	(1.31)	(3.73)	0.63	(4.12)	(1.56)
Recovery factor	0.41	(0.28)	(0.83)	(0.21)	(0.72)	0.26	(0.93)	(0.53)

I.6 Anomalies testing: Daily and Weekly-based portfolio net return best system based on the recovery factor

This table shows the net returns, in percentage, for both daily and weekly data. For each interval, we consider the compounded return of all positions opened until the last day, whether closed in that same year or in any other subsequent year. The returns are computed in money terms and correspond to the highest recovery factor of the best system.

Pair	AUD/NZD	AUD/USD	CAD/CHF	GBP/JPY
Daily				
	[19,39]	**[19,39]**	**[19,39]**	**[19,39]**
1995-2002	(23.35)	32.95	26.52	24.46

2003-2008	59.46	(24.84)	(10.96)	40.40
2007-2009	30.12	12.89	(5.14)	7.97
2009-2016	3.74	(4.06)	(22.14)	(25.80)
		Weekly		
	[6,19]	**[19,39]**	**[12,26]**	**[19,39]**
1995-2002	(4.74)	62.08	12.68	(34.13)
2003-2008	14.12	44.54	62.68	55.68
2007-2009	(4.29)	38.80	(11.52)	16.00
2009-2016	2.09	(26.22)	(30.19)	6.41

I.7 Portfolio net return of the best system

This table shows the yearly and weekly-based net returns, from 1994 to 2016. For each interval, we consider the compounded return of all positions opened until the last day, whether closed in that same year or in any other subsequent year. The returns are computed in money terms and correspond to the highest recovery factor of the best system.

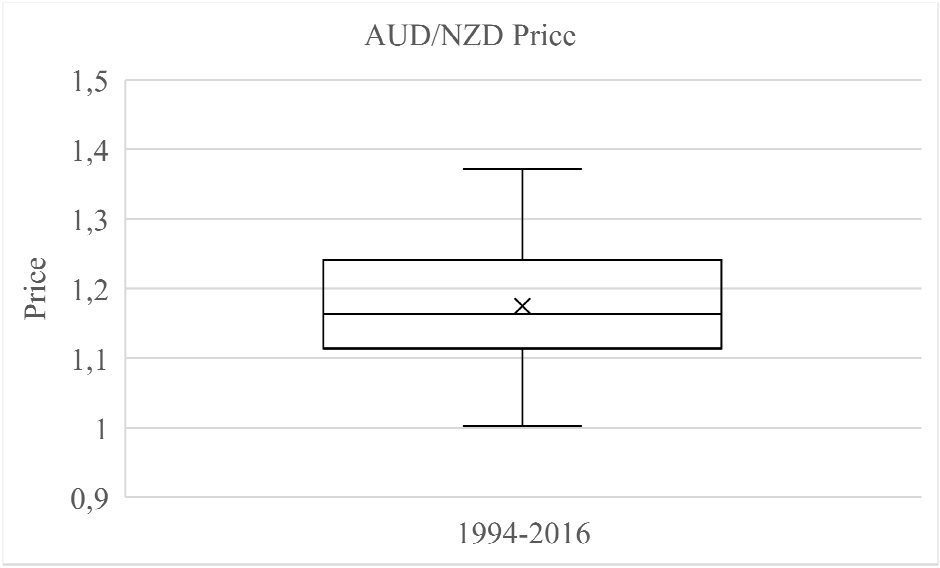
Panel A				
Pair	AUD/NZD	AUD/USD	CAD/CHF	GBP/JPY
		Daily		
	[19,39]	**[19,39]**	**[19,39]**	**[19,39]**
1994	3.79	(3.65)	(0.93)	12.72
1995	6.98	5.32	(1.55)	6.67
1996	(0.07)	7.24	3.84	(0.63)
1997	(2.79)	(11.54)	7.87	14.46
1998	(6.38)	(21.85)	(1.27)	5.29
1999	(9.24)	(9.32)	(6.52)	9.93
2000	2.26	19.76	15.68	(8.15)
2001	(2.11)	30.58	16.45	(11.66)
2002	(13.29)	(9.59)	(7.71)	9.23

2003	1.87	(26.11)	5.19	20.84
2004	(1.52)	12.56	(8.96)	10.24
2005	17.88	4.95	(5.79)	(2.91)
2006	2.84	(3.32)	(1.55)	(1.97)
2007	9.88	29.55	11.27	(11.75)
2008	19.33	(31.24)	(9.91)	25.49
2009	(0.76)	26.75	(5.37)	(2.51)
2010	4.16	(1.44)	(6.80)	6.44
2011	(1.06)	(4.09)	(5.57)	6.29
2012	(0.41)	10.91	(2.17)	(12.60)
2013	(16.49)	(3.28)	(9.34)	(6.94)
2014	5.52	(16.82)	8.11	1.18
2015	4.52	(5.69)	(1.94)	(0.03)
2016	10.59	(4.84)	0.56	(18.22)
		Panel B		
		Weekly		
	[6,19]	**[19,39]**	**[12,26]**	**[19,39]**
1994			(2.27)	
1995	2.85	22.81		
1996			16.53	(26.42)
1997	7.99		8.96	(5.52)
1998	(3.39)	10.10	8.60	16.30
1999	(4.67)	7.71		(12.26)
2000	4.13	(14.01)	2.48	9.83
2001	(14.20)	40.50	(14.51)	(12.69)
2002	4.24	(7.89)	(4.57)	(3.17)
2003	4.00		16.85	(1.44)
2004	8.86			
2005		4.13	20.45	18.79

2006	6.13		11.11	2.49
2007	1.56	(21.40)		32.82
2008	(6.92)	76.59	4.03	(2.32)
2009	1.25		(14.95)	(10.59)
2010	12.91	(14.07)	(19.14)	(10.41)
2011	(2.92)		4.10	26.46
2012	(11.56)	(1.74)	(2.13)	
2013	0.33	95.76	(8.92)	(8.50)
2014	5.63		8.60	14.81
2015	5.82	(8.76)	0.22	
2016	(3.46)		0.50	

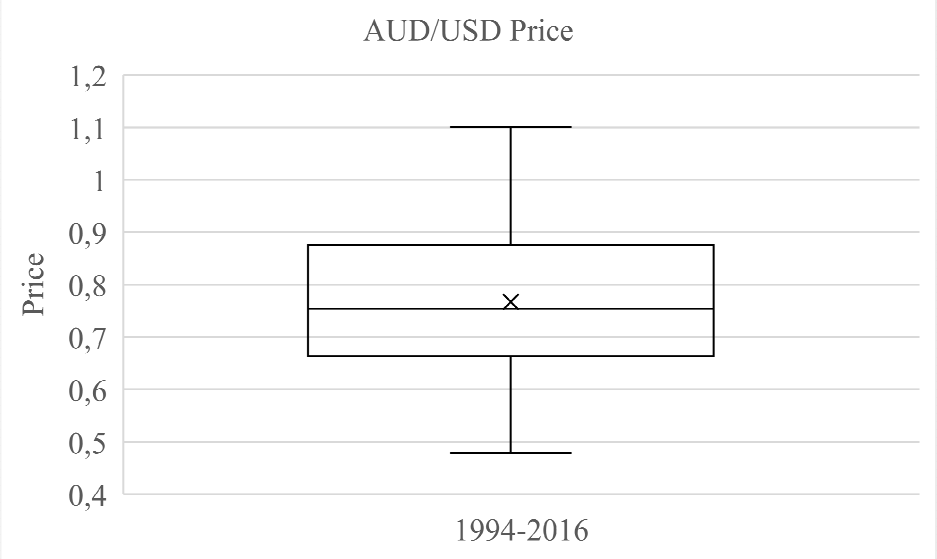
Appendix II – Descriptive analysis

II.1 AUD/NZD Descriptive statistics	
Mean	1.17500
Median	1.16380
Standard deviation	0.08000
Kurtosis	-0.95000
Skewness	0.18000
Range	0.36968
Minimum	1.00224
Minimum date	2015/04/03
Maximum	1.37192
Maximum date	2011/03/04
Close starting point	1.21830
Close ending point	1.03921



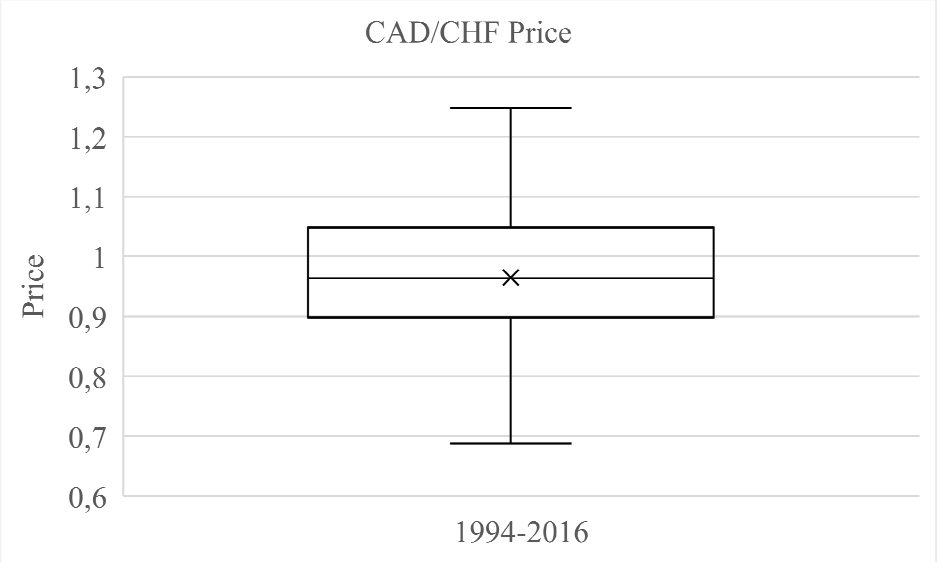
II.2 AUD/USD Descriptive statistics	
Mean	0.76690
Median	0.75390

Standard deviation	0.15
Kurtosis	-0.57
Skewness	0.26
Range	0.62171
Minimum	0.47870
Minimum date	2001/04/02
Maximum	1.10041
Maximum date	2011/07/28
Close starting point	0.68540
Close ending point	0.72040

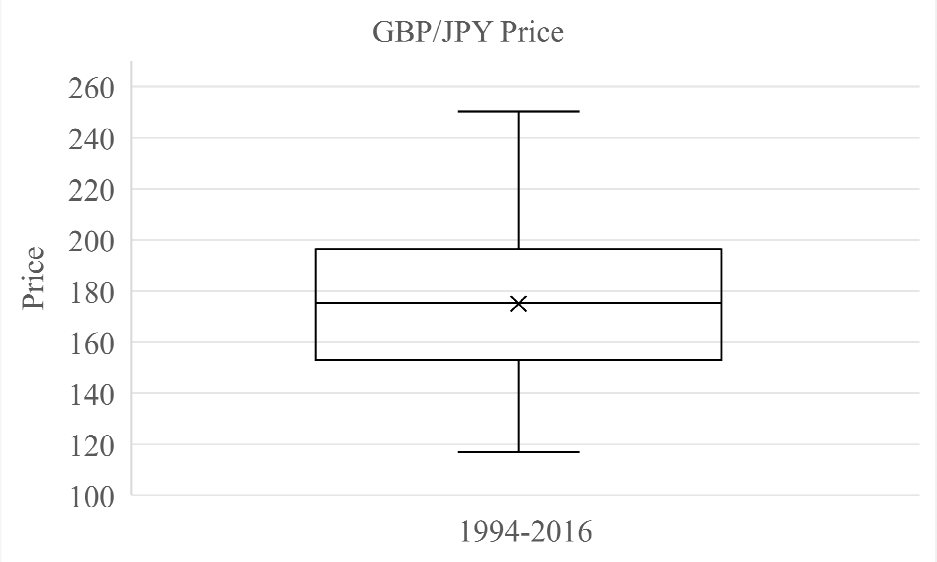


II.3 CAD/CHF Descriptive statistics	
Mean	0.96510
Median	0.96390
Standard deviation	0.11
Kurtosis	-0.49
Skewness	-0.24
Range	0.56013
Minimum	0.68777

Minimum date	2016/01/15
Maximum	1.24790
Maximum date	2007/11/06
Close starting point	1.1368
Close ending point	0.75768



II.4 GBP/JPY Descriptive statistics	
Mean	175.010
Median	175.245
Standard deviation	30.20
Kurtosis	-0.72
Skewness	0.10
Range	133.243
Minimum	116.967
Minimum date	2011/09/22
Maximum	250.210
Maximum date	2007/07/18
Close starting point	166.48
Close ending point	144.087

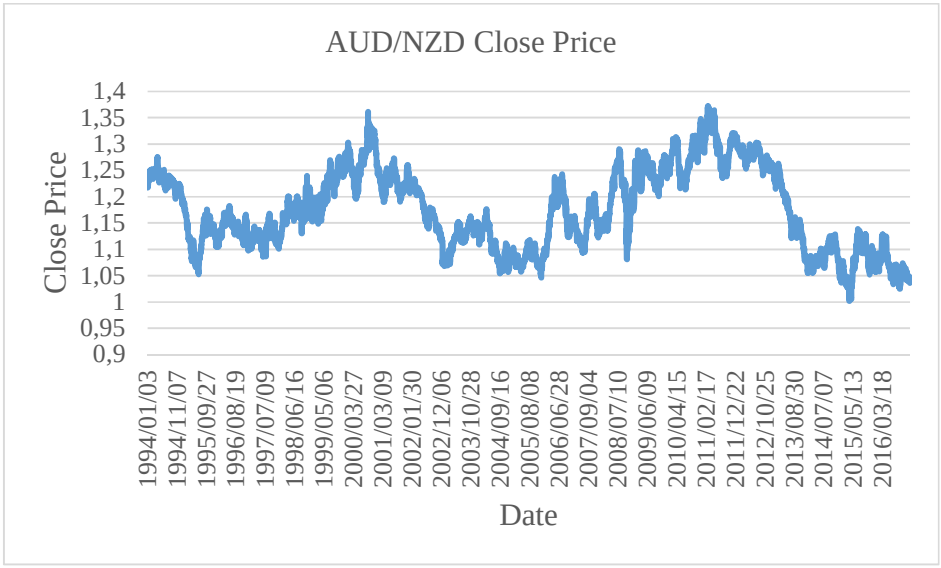

GBP/JPY Price
260
240
220
200
180
160
140
120
100
Price
1994-2016

Appendix III - Currency pairs' correlations

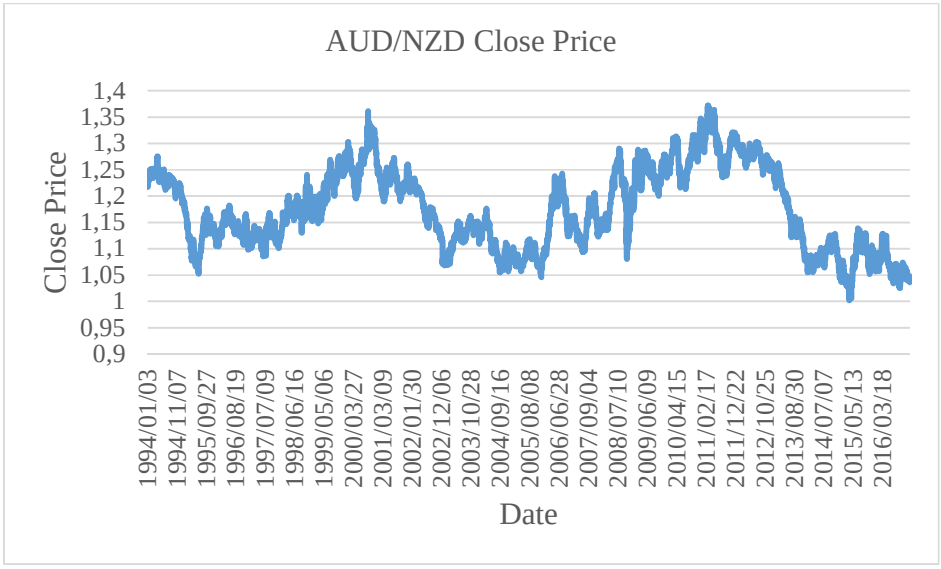
Daily forex returns' correlations				
Pair	AUD/NZD	AUD/USD	CAD/CHF	GBP/JPY
AUD/NZD	1.00	-0.22	0.38	-0.37
AUD/USD	-0.22	1.00	-0.59	-0.37
CAD/CHF	0.38	1.00	1.00	0.36
GBP/JPY	-0.37	-0.37	0.36	1.00

Appendix IV – Price action graphs

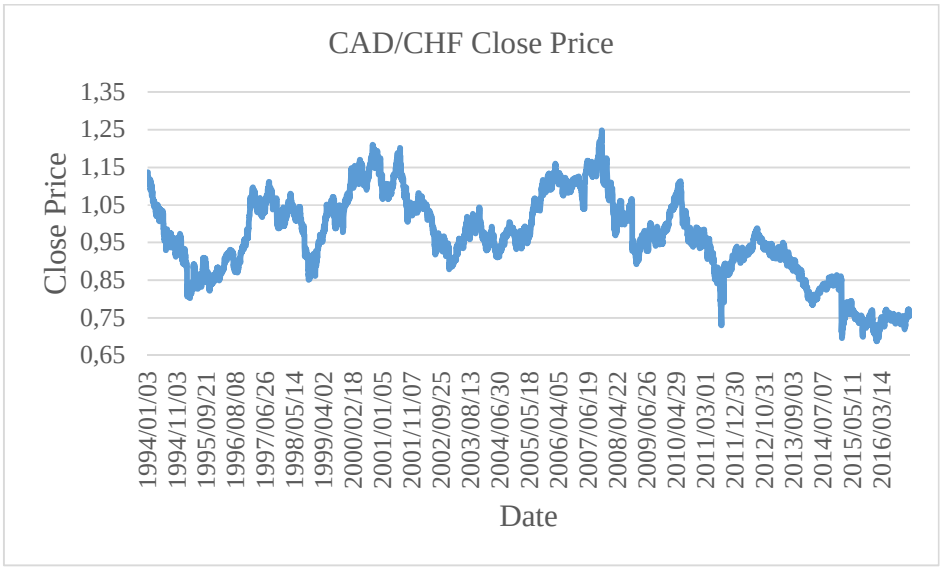
IV.1 AUD/NZD



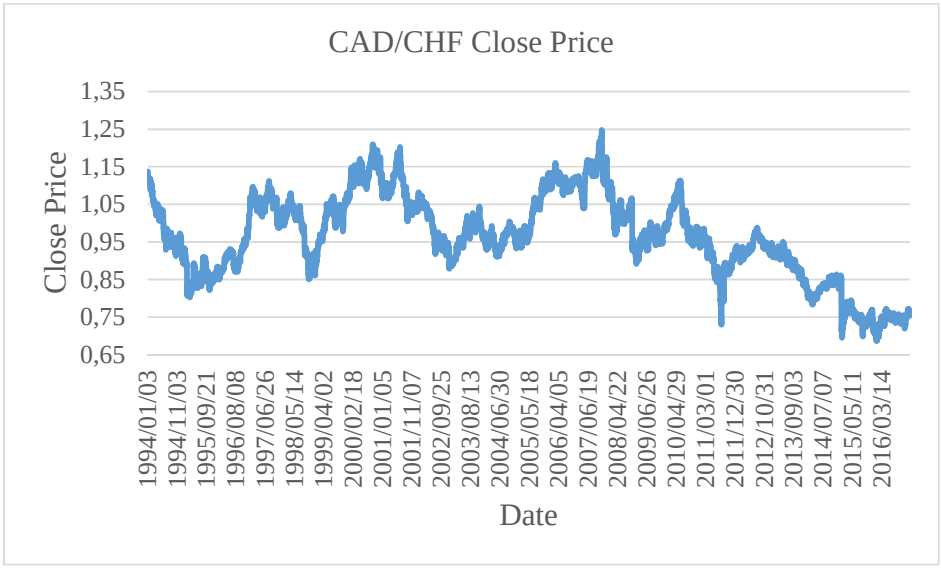
IV.2 AUD/USD



IV.3 CAD/CHF


CAD/CHF Close Price
Close Price
1,35
1,25
1,15
1,05
0,95
0,85
0,75
0,65
1994/01/03
1994/11/03
1995/09/21
1996/08/08
1997/06/26
1998/05/14
1999/04/02
2000/02/18
2001/01/05
2001/11/07
2002/09/25
2003/08/13
2004/06/30
2005/05/18
2006/04/05
2007/06/19
2008/04/22
2009/06/26
2010/04/29
2011/03/01
2011/12/30
2012/10/31
2013/09/03
2014/07/07
2015/05/11
2016/03/14
Date

IV.4 GBP/JPY


CAD/CHF Close Price
Close Price
1,35
1,25
1,15
1,05
0,95
0,85
0,75
0,65
1994/01/03
1994/11/03
1995/09/21
1996/08/08
1997/06/26
1998/05/14
1999/04/02
2000/02/18
2001/01/05
2001/11/07
2002/09/25
2003/08/13
2004/06/30
2005/05/18
2006/04/05
2007/06/19
2008/04/22
2009/06/26
2010/04/29
2011/03/01
2011/12/30
2012/10/31
2013/09/03
2014/07/07
2015/05/11
2016/03/14
Date

Appendix V - FxPro Group Limited brokerage house

As stated from the beginning, FxPro is the main broker used to collect relevant data for this work, namely the bid-ask spread and the swap rates retrieved for the different currency pairs used. For this work, it is considered the forex market's benchmark broker, because it a world-renowned enterprise for its forex services' quality and countless recognition and innovation-related attributed awards.

It was founded in 2006, registered in Limassol, however its headquarters are located in the City of London, London, United Kingdom. It is the holding company of FxPro UK Limited that is authorized and regulated by the Financial Conduct Authority (FCA) and FxPro Financial Services Limited that is authorized and regulated by Cyprus Securities and Exchange Commission (CySEC) and authorized by the South Africa Financial Services Board (FSB). As such, it is required to provide periodic financial reports certified by independent third party auditors. Also, FxPro Group Limited is a member of the following organizations: Cyprus Chamber of Commerce and Industry (CCCI), Cyprus Financial Services Firms Association (CFSFA) and Financial Services Compensation Scheme (FSCS). The company's online forex arm, initially registered as EuroOrient Securities & Financial Services Limited and now called FxPro Financial Services Limited provides online forex brokerage services to both institutional and retail clients. Under the European Union Markets in Financial Instruments Directive (MiFID) of 2004, FxPro Financial Services Limited and FxPro UK Limited can provide their services in the European Economic area.

FxPro provide their clients, in more than 150 countries, the following contract for difference (CFD) instruments: forex, futures, indexes, shares and commodities (metals and energies). Altogether, they comprise over 275 financial instruments as of March 2017.

The company provides their FxPro Financial Services Limited clients, the possibility to copy automatically other traders' strategies through FxPro SuperTrader platform, however there is a minimum first-time deposit requirement of $10,000, a minimum amount to copy of $500 and a maximum leverage of 1:200.

For MT4 and cTrader platforms, FxPro provides FxPro Quant that is a web-based strategy builder that allows clients to automate trading strategies by programming their own algorithms, expert advisors and cbots, respectively, without the use of a coding language.
For clients interested in automated trading, the enterprise gives access to the FxPro VPS, which is provided by BeeksFX, the largest provider of VPS solutions for automated trading. It is a service that gives access to a virtual private server, which allows to load algorithms coded in either MQL4, MQL5 or C#, directly onto the server, with reduced latency and without requiring that the computer is running.

FxPro is a non-dealing desk (NDD), ECN/STP broker, therefore using the "A booking" system. It means that the firm acts solely as an intermediary of each transaction, sending the clients' trading orders directly to the interbank market, liquidity providers or multilateral trading facilities (MTFs). So, in this case, there is no conflict of interest.

In terms of trading platforms, FxPro provides the Metatrader 4 and 5, developed by MetaQuotes Software Corporation, the market leader in retail forex, and the cTrader, developed by Spotware, an emerging trading software developer. The last addition is the FxPro Markets platform. All the platforms are also available for smartphones with iOS (Apple) and Android (Google) operating systems.

To clients' protection and full transparency, FxPro segregates clients' funds in different bank accounts in some of the most trustworthy and stable financial institutions, namely, Barclays PLC, Julius Baer Bank, Bank of America and Royal Bank of Scotland. Just as important, their clients of FxPro UK are insured by the Financial Services Compensation Scheme (FSCS) up to £50,000 per client and clients of FxPro Financial Services Limited are insured by the Investor's Compensation Fund (ICF) up to €20,000 per client. On the other hand, clients benefit from negative balance protection, preventing their balances from dropping below zero at FxPro's expense.

Currently, the company does not accept accounts openings from Canada, Iran and USA.

Appendix VI - MACD Divergence Strategy in R programming language

Application:

```
nomedoFicheiro = "GBPJPY2.xlsx"
nomedaFolha = "Sheet2"

library(xlsx)

duracao=proc.time()
d <- read.xlsx(nomedoFicheiro, 1, sheetName = nomedaFolha, stringsAsFactors = FALSE)
#1-id  2-Date 3-High  4-Low  5-Close  6-MACD

print(paste("tamhano da entrada: ", nrow(d)));
tipo = character()
id_f = integer()
id_i = integer()
fecho_dseg = integer()

for (n in 2:(nrow(d) - 2)) {
   #n: id_i da frame de análise
   mr = d[n, 6]
   if (mr > d[n - 1, 6] & mr > d[n + 1, 6]) {
      # mr: maximo local de macd na posicao n
      hr <- d[n, 3]
      i = n
      while (i < nrow(d) - 1) {
         i=i+1
         m = d[i, 6]
         if (m > d[i - 1, 6] & m > d[i + 1, 6]) {
            # m: maximo local de macd na posicao i
            h = d[i, 3]
```

```
            fechods = d[i + 1, 5]
            if (m < mr & h > hr & h > fechods) {
               # n->i: intervalo Higher high
               tipo = c(tipo, "HH")
               id_f = c(id_f, i)
               id_i = c(id_i, n)
               fecho_dseg = c(fecho_dseg, fechods)
               i = nrow(d)
            } else if (m > mr & h < hr & h < fechods) {
               # n->i: intervalo Lower high
               tipo = c(tipo, "LH")
               id_f = c(id_f, i)
               id_i = c(id_i, n)
               fecho_dseg = c(fecho_dseg, fechods)
               i = nrow(d)
            }
         }
      }
   } else if (mr < d[n - 1, 6] & mr < d[n + 1, 6]) {
      # mr: minimo local de macd na posicao n
      lr <- d[n, 4]
      i = n
      while (i < nrow(d) - 1) {
         i = i + 1
         m = d[i, 6]
         if (m < d[i - 1, 6] & m < d[i + 1, 6]) {
            # m: minimo local de macd na posicao i
            l = d[i, 4]
            fechods = d[i + 1, 5]
            if (m < mr & l > lr & l > fechods) {
```

```
                # n->i: intervalo Higher low
                tipo = c(tipo, "HL")
                id_f = c(id_f, i)
                id_i = c(id_i, n)
                fecho_dseg = c(fecho_dseg, fechods)
                i = nrow(d)
              } else if (m > mr & l < lr & l < fechods) {
                # n->i: intervalo Lower low
                tipo = c(tipo, "LL")
                id_f = c(id_f, i)
                id_i = c(id_i, n)
                fecho_dseg = c(fecho_dseg, fechods)
                i = nrow(d)
              }
            }
          }
        }
}
id_interv = id_i * 1000000 + id_f;
df = data.frame(id_interv, tipo, id_i, id_f, fecho_dseg, stringsAsFactors = FALSE)
df <- df[order(id_f, id_i),];

#df-> 1-id_interv  2-tipo  3-id_i  4-id_f  5-fecho_dseg

id_int = integer()
posicao = character()
paberta = "nula"

linha = 1
ll = linha
```

```
while (ll <= nrow(df)) {
   id_int = c(id_int, df[linha, 1])
   idf = df[linha, 4]
   if (df[linha, 2] == "HH" | df[linha, 2] == "LH")
      if (paberta == "Vender") posicao = c(posicao, "")
      else {posicao = c(posicao, "Vender"); paberta = "Vender"; }
   else
      if (paberta == "Comprar") posicao = c(posicao, "")
      else {posicao = c(posicao, "Comprar"); paberta = "Comprar"; }
   ll = linha + 1;
   while (ll <= nrow(df) & df[ll, 3] <= idf) { ll = ll + 1 }
   linha = ll
}

tipo = character()
id_i = integer()
data_i = character()
high_i = integer()
low_i = integer()
close_i = integer()
macd_i = integer()
id_f = integer()
data_f = character()
high_f = integer()
low_f = integer()
close_f = integer()
macd_f = integer()
fecho_dseg = integer()
fecho_dseg_ant = integer()
retorno = integer()
```

```
for (id in id_int) {
   tipo = c(tipo, df[df$id_interv == id, c('tipo')]);
   id_i = c(id_i, df[df$id_interv == id, c('id_i')]);
   data_i = c(data_i, d[d$id == id_i[length(id_i)], c('Date')]);
   high_i = c(high_i, d[d$id == id_i[length(id_i)], c('High')]);
   low_i = c(low_i, d[d$id == id_i[length(id_i)], c('Low')]);
   close_i = c(close_i, d[d$id == id_i[length(id_i)], c('Close')]);
   macd_i = c(macd_i, d[d$id == id_i[length(id_i)], c('MACD')]);
   id_f = c(id_f, df[df$id_interv == id, c('id_f')]);
   data_f = c(data_f, d[d$id == id_f[length(id_f)], c('Date')]);
   high_f = c(high_f, d[d$id == id_f[length(id_f)], c('High')]);
   low_f = c(low_f, d[d$id == id_f[length(id_f)], c('Low')]);
   close_f = c(close_f, d[d$id == id_f[length(id_f)], c('Close')]);
   macd_f = c(macd_f, d[d$id == id_f[length(id_f)], c('MACD')]);
   fecho_dseg = c(fecho_dseg, df[df$id_interv == id, c('fecho_dseg')]);
   if (length(tipo) > 1) { fecho_dseg_ant = c(fecho_dseg_ant, fecho_dseg[length(fecho_dseg)
- 1]) }
   else { fecho_dseg_ant = c(fecho_dseg_ant, NA) };
   if (tipo[length(tipo)] == "HL" | tipo[length(tipo)] == "LL") { retorno = c(retorno,
(fecho_dseg[length(fecho_dseg)] / fecho_dseg_ant[length(fecho_dseg_ant)] - 1)) }
   else { retorno = c(retorno, (1-fecho_dseg[length(fecho_dseg)] /
fecho_dseg_ant[length(fecho_dseg_ant)])) };
}

df2 = data.frame(id_int, tipo, id_i, data_i, high_i, low_i, close_i, macd_i,
    id_f, data_f, high_f, low_f, close_f, macd_f, fecho_dseg, fecho_dseg_ant, retorno,
posicao, stringsAsFactors = FALSE)
write.xlsx(df2, nomedoFicheiro, sheetName = paste(nomedaFolha, "R", sep = "_", collapse
= NULL), append = TRUE, row.names = FALSE)
```

```
print(proc.time() - duracao);
```

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