Technical Performance Analysis of FX trading strategies

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Abstract (English)

In this project I will analyze and incorporate one of the most popular foreign exchange trading strategies in use, also known as carry-trading. Using this strategy the trader attempts to capture an interest differential between a low yielding currency, and a higher yielding currency. Selling the currency with the lower interest rate and buying into the one with the higher interest. The greatest risk is the movement of the currency exchange rates, which if not accounted for properly, could amount into a major loss. Another known strategy for trading FX products is the momentum strategy. This is a strategy which tries to utilize and take advantage of market movements. Based on the theory of supply and demand you assume that the exchange rate with go and down concurrently with large transactions of the particular currency. I.e. If many people buy a certain asset the price would rise, and vice-versa if selling would occur. The idea of momemtum is to capture the up and downtrends of hte market. The question I seek to answer, is whether it is possible to optimize and utilize these strategies to make a significantly risk-adjusted profit.

Summary (Danish)

Dette projekt har til opgave at undersøge forskellige handelsstrategier i valutamarkedet. Som hovedemne i opgaven er 'carry-trading' i fokus. Hvilket er en strategy der indebærer at man forsøger at lukrere på forskellen mellem renterne i hvert af de valutaer man har i sin portfølge. Eksempelvis kunne man gå kort (sælge) i tre af de mindst forrentede valuta, og modsat gå langt (købe) tre af de valuta med højest rente. På denne måde ville forskellen mellem renterne kunne generere afkast, såfremt at der ikke måtte ske for store kursudsving under vejs. En anden strategi der har vist sig at være bæredygtig i nogle henseender er 'momentum'-strategien. I denne strategi forsøger man at fange de større trends i markedet som eksempelvis kan gøres vha. simple moving-averages. Hovedsagligt baserer den sig på fundamentale markedsprincipper som udbud og efterspørgsel, man antager at kursen på en given valuta stiger og falder proportionalt med hhv. køb og salg af det enkelte værdipapirer.

Altså vil opgaven undersge om det umiddelbart er muligt at optimere og blande disse strategier, således at denne har et signifikant risiko-justeret afkast. Alle strategier af vilkårlig variation er alle modificeret versioner af den simple carry-trade strategy.

Preface

This thesis was prepared at the department of Informatics and Mathematical Modelling at the Technical University of Denmark as a bachelorsproject under the supervision of Murat Kulachi (IMM), and Kourosh Manjani (MAN). The project has been undertaken during the period 1st of june 2012 to 31st of august 2012. It is written by Maxim Khomiakov.

The thesis deals with the foreign exchange market and the profitability thereof. By utilizing known theories and working on actual and recent data material i seek to discover whether or not a certain profitability is possible.

This report is possible to read without any knowledge of the subject at matter. However, it would prove to help the understanding if the reader has some knowledge on basic statistics and linear regressions. It would also be beneficial to have a knowledge of R and MatLab since attached code printouts might help understanding the implementation and the acquired results to a better degree.

The thesis consists of 5 Chapters and 64 pages.

Lyngby, 31st-August-2012

Maxim Khomiakov

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I would like to thank my supervisors, Associate Professor Murat Kulachi (IMM), and Associate Professor Koroush Manjani Rasmussen (MAN) for all the support and interesting discussions. For all the guidance and inspiring comments, which has been given throughout the project lifespan. Especially when adressing difficulties in the data I have been very fortunate to gain support from my supervisors. Furthermore I would like to thank MSc.-students Adam Westergaard and Peter Bundsgaard for all the interesting debates, support and for providing with a great framework to build the strategies upon.

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CHAPTER 1

Introduction to the foreign exchange market

The foreign exchange market. The most liquid market as of today. The amount of trades being done continuously are many. The current trading capitalization on the FX-market daily (Apr. 2010) is around \$4 trillion. The currencies fluctuate many times at a constant. But the cause of the different movements on this market are not always possible to correlate with a specific event. There are in fact, quite many occasions, historically speaking where an appreciation or depreciation of a particular currency was not possible to perfectly link to certain happenings.

We do know for a fact however, that the nominal exchange rate of a currency is determined by several macroeconomic factors. That is, the interest rate R, the money supply M^s and the money demand M^d of a particular currency, see Krugman, Obstfeld,Melitz (2012) The money supply and the interest rate are being determined by the home country's governmental financial institution. In the case of European euro-implemented countries this acting institution would be the ECB (European Central Bank).

Speaking from a macroeconomic point-of-view, you would strive to set the previously mentioned factors according to the national economical balance of that country or region. You are not interested in your goods being priced to high, neither would you want to lose profit by pricing the goods too low. Therefore the balance of these factors are essential for a healthy economy in any country.

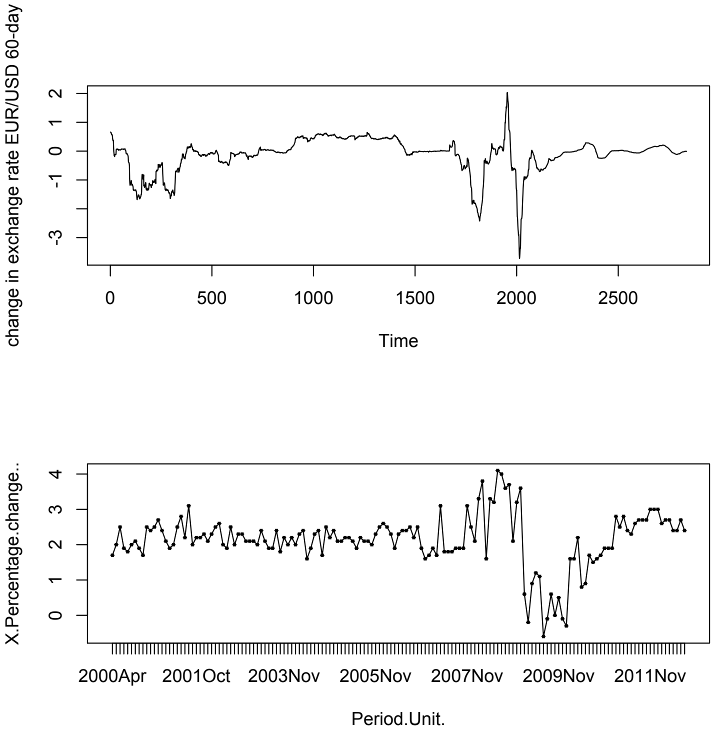

Figure 1.1 EUR/USD Spot rates (60-day), ECB PPP data ×% change in EUR/USD

Another interesting macroeconomic factor which tends to impact the exchange rates is the Purchasing Power Parity (PPP). The PPP is an indicator of consumer purchasing power in relative to other countries. In fact it is economically, a basket of pre-determined available goods, which is then compared by price among other countries. A good example of this is the 'Big Mac Index'. Using the price of a commodity available in most countries around the world, you would have an idea of relative price levels around the world. It so happens to be a good indicator of exchange rate movements in the future, as well. 1.1 shows correlated movements in the changes of exchange rates and changes in the PPP.

The actors on the FX-market however, are not only buyers and sellers of physical goods. A large majority of the daily trade volume is made from professional speculators. Institutions such as commercial banks, corporations, the nonbank financial institutions (hedge funds, brokerage firms), and the governmental central banks. In such a market it is highly difficult for an ordinary investor to generate a profit. There are however quite a few strategies which has proved to work for some. Some of these strategies we will try to analyze and review for risk and return opportunities.

Working with the foreign exchange markets, you could add a vast amount of data and economic variables. Many variables are best using under certain scopes. E.g. Data such as the real exchange rates and real interest rates are one of such variables which make little sense on anything but the long term. Similarly the nominal exchange rates are usually being used in short term time frames. The difference in these analytical frames are the number of variable factors in play. In the short run atleast one factor is fixed, in the long run all factors are variable.

Therefore, in order to set the scene, my focus in the project is usually based on short run assumptions and scopes. The foreign exchange market is also specifically characterized by its highly frequent short-term held positions.

1.1 Spots, Forwards & Swaps

One of the many different options when concurring a trade in the foreign exchange market is by utilizing certain risk-adjusting contracts. Among the most common is the spot contract. A spot contract involves a currency trade between to parties at the present price of the currency. In other words, on the exact minute or second the trade is agreed upon. The spot contract is considered a risk-free transaction since it occurs momentarily and thereby the risk of default or non-delivery is virtually in-existent. This is due to the current technological state of the financial market, in which most securities are traded electronically and thereby momentarily.

Another frequent way of making a trade, is by buying a forward contract. A forward contract essentially is a Spot-contract except the delivery date of the currency is set in the future. This time period could be 30, 90 or 180 days. Since forward contracts are OTC(Over the counter) products, anything the two parties would agree upon is what they are to execute. Forward contracts are highly valuable when adjusting for currency-risk. Suppose you were in charge of signing an export agreement with a client of a foreign country. In your country you are used to settling payments in EUR, in this case however the client would like to pay you in their own domestic currency, USD. The export is due to take place immediately however, the payment is due in 3-months. How can you assure that the value of your goods are not deflated by currency-fluctuations? You could endure in a forward contract. e.g assume a 90-day forward contract

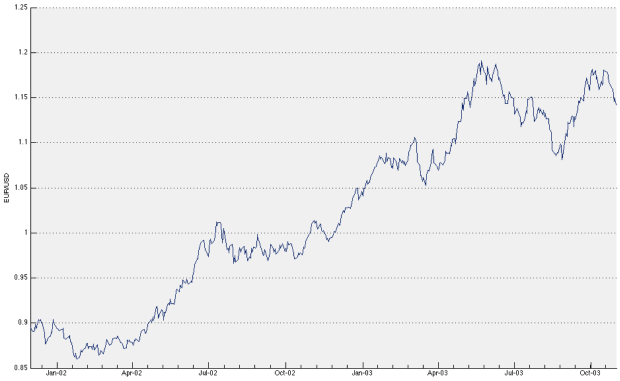

Figure 1.2 EUR/USD Spot rates

the payment which is due is $1,000,000 which at the time (02/04/2002) amounts to €880,600. On (02/07/2002) the same amount of USD is equal to €986,500, all other things equal this would incur an opportunity cost (loss of profit) of −105,900[1]. As this example shows, fixing the exchange rate is not always the most profitable option.

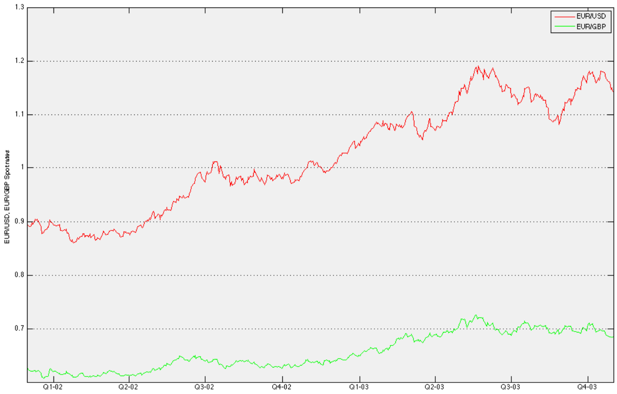

Figure 1.3 EUR/USD, EUR/GBP Spot rates

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[1] Based on the EUR/USD Spot rate of 0.8794 (02/04/2002) and 0.9865 (02/07/2002)

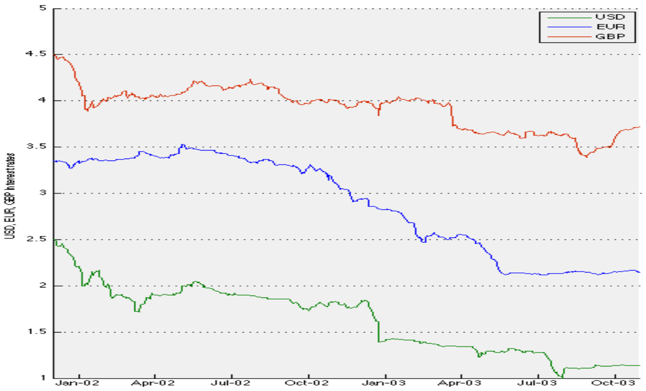


Figure 1.4 Top to bottom, GBP, EUR, USD Interest rates

Swap transactions are combinations of both of the above.In a foreign exchange swap you would perform a spot sale of a foreign currency, and a forward repurchase of the same amount and currency somewhere in the future. The foreign exchange swap contracts are also OTC securities therefore they are not included on big exchanges. Going back to the previous example, a more economically wise choice for the company would be the swap option. The transaction costs are higher when incurring two separate transactions than when creating a swap.

When working with nominal exchange rates, all other things equal, an increase in the interest rate of a currency, would result in an appreciating currency. Likewise currencies with decreasing interest rates would result in decreasing nominal exchange rates. Therefore, many traders analyze exchange rates in relation to the interest rates. So when buying a forward contract, or a swap contract, the rate of depreciation/appreciation

$$\frac{R_{HC/FC}}{R_{FC/HC}} \tag{1.1}$$

is an important measure when calculating the price of the contract. HC and FC stand for home country and foreign country respectively, and R in this case is the interest rate.

E.g, when looking at figure 1.2, and 1.3. In figure 1.2 you would assume the USD to appreciate slightly above the EUR, but nothing very certain. However, when looking at 1.3, you clearly see how the EUR interest rate spikes in compared to the GBP interest rate. Therefore you would expect the EUR/GBP rate to appreciate as a result of the latter. Looking at 1.4 the red line shows the

EUR/USD spot rates, this graph shows appreciation of the USD to the EUR, with a fair amount of variance. The green line, being the EUR/GBP exchange rate, is showing a steady appreciation against the EUR.

1.2 The Carry Trade

One of the key topic of analysis in this thesis, is the carry trade strategy. It is a fairly simple trading strategy which employs exploitation of interest rate differentials in the foreign exchange market. By utilizing a high interest rate of a certain currency, you would go long (invest) in that particular currency, with a funding currency which you would short (sell) simultaneously. Thereby the money invested in the investment currency would appreciate by the interest rate differential $\Delta i = i_{\$} - i_{EUR}$.

Two important economic factors are relevant to introduce when discussing the carry trade strategy. The interest parity condition.Uncovered Interest Parity (UIP) implies that the home interest rate should equal the foreign interest rate plus the rate of depreciation of the home currency. If UIP holds, if would seem to rule out the naive strategy of borrowing in a low interest rate currency and investing in a high interest currency, investment referred to as a carry trade. UIP implies that the expected profit from such trades is zero. That is, if we have two countries currencies offering different interest rates on their deposits, investors would shift their money to the currency which offers the highest rate of return. This would then balance out the differences over time. Formally this is expressed by the equation:

$$(1 + i_{EUR}) = (1 + i_{USD})\frac{E^e_{EUR/USD}}{E_{EUR/USD}} \tag{1.2}$$

Where $E^e_{A/B}$ is the expected future rate of the spot rate.

Covered Interest Parity (CIP) describes a similar situation to the UIP condition, however when UIP is concerned with the spot rates, the CIP is concerned with forward rates. The CIP condition states, that interest rates between to countries are dependant on the forward rate and the spot rate of the currency pair.

$$1 + i_{EUR}) = (1 + i_{USD})\frac{F_{EUR/USD}}{E_{EUR/USD}} \tag{1.3}$$

. The opportunity for profit in this scenario would be when you wanted to lock exchange rates into a future date, earning both an interest rate and the gain (or loss) of the deposit currency which you buy a forward upon. The scenarios are either to gain, or to lose, or in the third case, neither. This is what is expressed by the CIP equation.

In order for carry trading to be possible (with a profit margin), the UIP should not hold. Which research shows, is also rarely the case. See Feenstra Taylor (2011). In this thesis we will incorporate the G10 strategy which is basing its profit on the violation of the UIP condition.

CHAPTER 2

Theory on the financial markets

In order to understand the calculations and the movements in financial market I will introduce a few useful formulas. Since the primary focus of this thesis is on carry trading, basic bond theory is important to understand. Carry trading involves using a low-bearing interest currency to invest in a high interest bearing currency. The security in which you invest is the treasury bonds of that particular country. You calculate the return on a treasury bill by

$$\frac{\text{Face value}}{(1+i)^t} \tag{2.1}$$

Where face value is the principal, or the exact value being discounted at interest i to time t. Furthermore we use forward-rates to estimate and minimize foreign exchange risk when undergoing investments, in order to calculate the price of a forward contract by the following

$$\text{Price of a forward} = F_{A/B} = E_{A/B} + \frac{(1+i_A)\cdot(d/360)}{(1+i_B)\cdot(d/360)} \tag{2.2}$$

Where $E_{A/B}$ is the exchange rate between currency A and currency B, i_A is the interest rate of currency A, d is the contract length, and i_B is the interest of currency B. The relationship between the two interest rates and the length of the contract is sometimes being referred to as a forward premium (discount). This is because it is exactly what seperates a forward price from a simple exchange rate. In other words, it is the price (cost) of creating a forward contract. It also reflects the market expected price of the spot rate at a future date.

Forward contracts are fixed upon signing (purchase). Which means that you are not allowed to change your mind during the contract length period. However, if by any chance you are not satisfied with the contract you have undertaken, you can simply buy a new contract which bets against your initial contract.

E.g. If you were to undertake a contract between country A and B, and the locked exchange rate was 1.3 at initial purchase. Now 30 days later the exchange rate is 2.3, which means you are looking at a loss of 56% in gained value. Believing that the exchange rate will rise to a target price of 3.5 all of a sudden, you hastily want to buy a new contract. The price of the contract is in line with the formula stated above, that is

Shorting A technique in the financial market which is highly used is the concept of shorting an asset. By shorting you are borrowing an asset from an external party at a fee, in the hope of selling it lower than the going market price for a profit. In the foreign exchange market it would translate into borrowing a foreign currency, exchanging into home currency, and hoping the foreign currency to depreciate upon maturity of the loan.

Going Long Opposite from the former, going long on a particular investment meaning to invest into an asset, in the expectation of appreciation. When investing long you are buying the asset in question, however in the foreign exchange market this is usually done by very high leveraged margins. It is not uncommon for the margin investor to be leveraged 1:100. Thereby a 1% loss amounts to 100 $\times theamount(inabsoluteterms)becauseofthehighleverage.$

2.1 The G10 Strategy, a practical walkthrough

Because of liquidity and risk concerns, traders rarely trade in currencies which aren't traded in high volumes and frequent transactions. The G10 strategy is based on the group of ten countries of which are the most liquid and most traded currencies. Several factors are to be examined however. First of all we use the Spot exchange rates ($E_{HC/FC}$), the daily interbank interest rates ($R_{HC/FC}$).In our model our portfolio consists of 6 currency based securities. This portfolio would be balanced so that only three of the highest interest bearing, and three of the lowest interest bearing currencies would be included. The country exchange rates which are included in the G10 strategy is as follows.

EUR
USD
JPY
GBP
CHF
AUD
CAD
SEK
NOK
NZD

Representing the euro, us dollar, japanese yen, british pound, swiss franc, australian dollar, canadian dollar, swedish kronar, norwegian kronar, and the new zealad dollar.

The G10 carry trade strategy can be employed on a great variety of ways. The way I employ it is by having a portfolio of a maximum of six securities. It is never allowed to short/long in the base currency, that is the EUR. However, you can add that whenever all the money is not invested you indirectly go long on the EUR since you're gaining the EUR interest rate on EUR deposits. We frequently buy forward contracts to lock the exchange rates and to minimize the currency risk.

At day 0 you evaluate all currency on their interest rates and open long positions at the top 3 interest bearing currencies. Similarly you open three short positions at the bottom three. You reevaluate whether or not eh currencies in the portfolio infact are the low/highest interest bearing currencies once weekly. You can easily evaluate on whether or not the currency spot rate is expected to appreciate/depreciate. Since the forward premium or discount will tell you which exchange rate is expected in the future.

In the midst of revisions of your portfolio, you also open and close positions based on your impressions and thoughts on the market. If you would like to wind down a position you buy a forward contract in the opposite currency cross. The entry, take profit and re-entry conditions are solely up to the trader to decide. However I will go through a few technical indicators which can provide decisional support for trader when making these decisions. These are the same indicators we will simulate and analyze based on naive profitability. That is, acting on a sole technical indicator blindly throughout the period.

2.2 Technical indicators

Should i stay or should i go? Probably the most complicated in succeeding in the financial markets, is the question or whether or not to wind down the positions, or to open up some new. Here we will discuss some common indicators which assist the trader in making these decisions.

2.2.1 Momentum strategy

Based on the moving average of a currency pair. A moving average shows the average value of data during a certain time span. E.g. a MA(5) would tell the average values of data the past 5 days, and an MA(20) would do the same based on a horizon of 20 days. The formula for calculating the moving average is

$$\text{Simple MA} = \frac{\sum_{i=1}^{n} P_i}{n} \tag{2.3}$$

Where P is the price/value of a particular dataset, and n is the number of days the moving average should be evaluated. There is an old saying that you should buy until the moving average is above the current price level, and sell when the moving average is below the prices. This is also the definition of the momentum strategy, to catch the trend when going up, and start shorting it when going down.

2.2.2 EMA

The exponential moving average is a move sensitive tool than the simple MA. It addresses some of the simple MA flaws. Such as it does not jump in terms

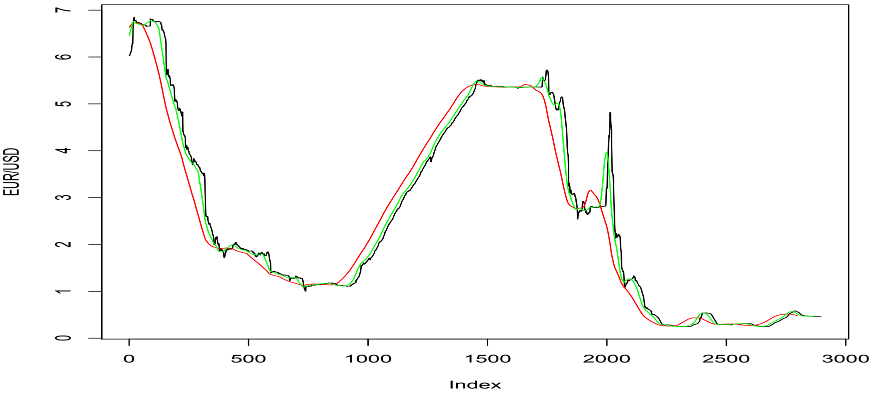


Figure 2.1 Spot rates of EUR/USD and an MA(100) red, and MA(30) green.

of old data, but at the same time it responds faster. It assigns a greater weight to the most recent trading day. E.g. In an EMA(10) the most recent closing price amounts for 18% of the total EMA value, compared to an MA all values are equal.

$$EMA = P_t \frac{2}{n+1} + EMA_{t-1}(1 - \frac{2}{n+1}) \tag{2.4}$$

Chosing the right period of the EMA is essential. A short period captures market movements very rapidly, at the expense of giving too many signals of trading action. A long lived EMA process will capture major trends, but fails to capture the short-lived fluctuations. The direction of the slope on the moving average shows the market overall trend. If the EMA rises it is best to go long, when it starts falling it is more profitable to go short.

2.2.3 Moving Average Convergence-Divergence (MACD)

Moving Average Convergence-Divergence is a series of EMAs (usually three) it appears as two lines, which when intercepting gives signals on buying or selling. Calculating the solid line you need to take the difference between two EMAs. E.g. Looking at 120 days worth of FX data, the first EMA would be set to 12, the next to 26. Then the difference in between them is plotted as the solid line. Another 9-day EMA is made by calculating the EMA of the solid line. This is the signal line. It is worth mentioning that when discussing the MACD in its most common form, the solid line is always the difference between EMAs of period 26 and 12. The signal line is also in the same case most commonly an EMA of the solid line with a 9-day period.

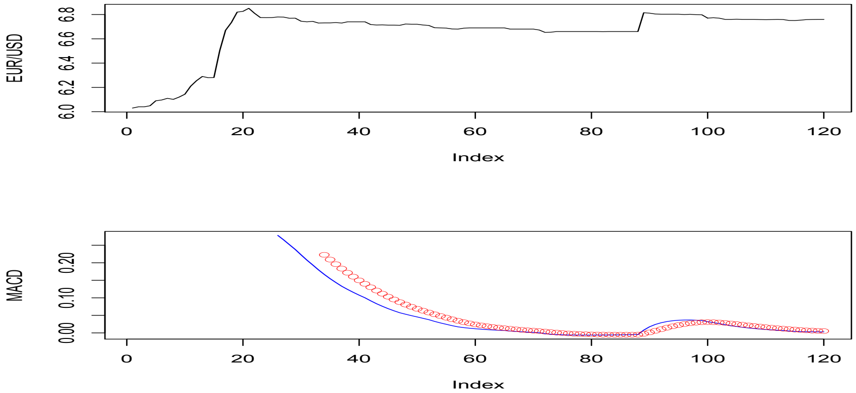


Figure 2.2 Spot rates of EUR/USD and MACD. Blue line solid (ΔEMA(26,12), Red data points is signal. EMA(9) of the solid line.

Usual trading rules when dealing with the MACD is looking at when the MACD line crosses the signal line or vice versa. The crossovers identifies balance shifts between bull and bear markets. Bull being the uptrend, and bear being the downtrend. The solid MACD line indicates the mass trend over a shorter period, the slow signal line reflects the mass trend over a longer period. Whenever the solid MACD line rises above the signal line, it indicates that it is a bullish market, and therefore it is advisable to go long. The opposite is the case whenever the MACD line falls below the signal line, and thereby shorting is the best indicated option.

2.2.4 Price Rate of Change

Price Rate of Change (or RoC) is a technical indicator which measures the trend acceleration. The speed of the gain or the loss. This gives a possibility of getting an idea of when trends are accelerating or slowing down. Usually you would see a peak before the trend reaches its high, and it would reach the bottom before hitting its low. Rate of Change compares todays closing price with a price on a former selected period. It divides the price of today, with the price of a former time.

$$RoC = \frac{P_t}{P_{t-n}} \tag{2.5}$$

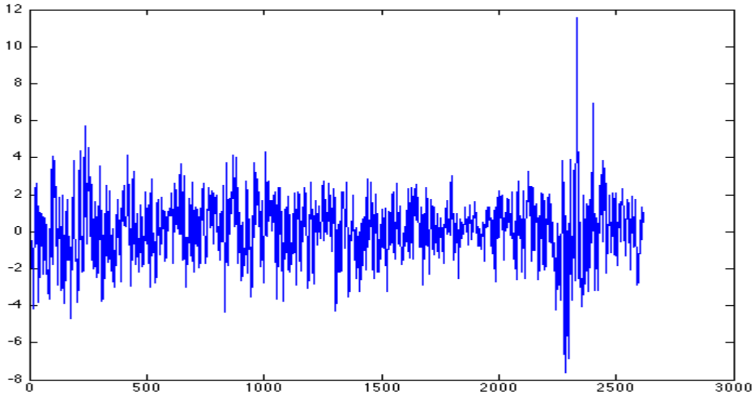


Figure 2.3 Spot rates of EUR/USD and RoC. Notice how at index 2500 the change is fairly high. This is the year of 2008, the recent financial crisis.

2.2.5 Relative Strength Index (RSI)

The relative strength index is an oscillator which measures the strength of a financial security by monitoring the changes in closing prices. It is also referred to as a coincident indicator, since it is not lagged indicator by one which reacts simultaneously.

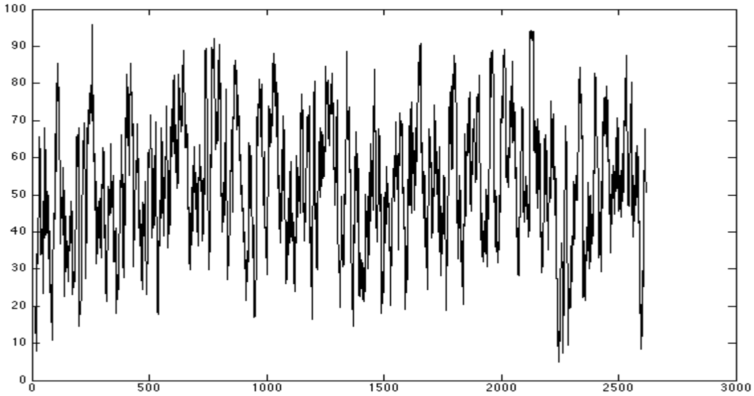


Figure 2.4 Spot rates of EUR/USD and the RSI.

The RSI fluctuates between 0 and 100. Whenever there is a positive to negative relative change in the RSI, it has identified a peak, and as it turns down, it identifies a top. In other words, the sign chance on the change is indicative of hills and valleys. Traders usually categorize the RSI-signals into different categories of importance.

The divergences between the RSI and the price are some of the strongest buy/sell signals. This is usually the case at the peaks and the lows. They appear when there is a weak trend and the trend is ready to reverse. When the peak or the low is reached is a matter of 'gut'-feeling. There is no exact quantitative solution to determining whether or not the chart has reached a major low/high.

CHAPTER 3

Analysis on the carry trade possibility

Now we have most of the basic theory in place in order to conduct the analysis in detail. The formulation of the UIP in Chapter 1 does still hold, however we will introduce some new variables which will prove to be a better measure of the latter. We log both the interest rates and the nominal exchange rates in order to make sure that a linear relationship can exist.

$$s_t = log(\text{nominal exchange rate at time } t) \tag{3.1}$$
$$\Delta s_{t+1} = s_{t+1} - s_t \tag{3.2}$$

The most commonly used UIP approximation, as described in Feenstra *et al* (2011), would be

$$i_A = i_B + \underbrace{\frac{\Delta E^e_{A/B}}{E_{A/B}}}_{\text{rate of de/appreciation of currency A}} \tag{3.3}$$

Where the left hand side is the interest rate on country A deposits, the first term on the right is the interest rate on country B deposits, and the last expression is the expected rate of depreciation of currency A. We use this approximation as a proxy for UIP since the original formulation expects knowledge of future expected spot rates. These include also sentiment of the trader, data which we do not have.

Since we are basing our analysis on historical data, we can reduce the expression to a simple difference in the exchange rate at time $t+1$. That is,

$$\frac{\Delta E^e_{A/B}}{E_{A/B}} = \Delta s_{t+1} \tag{3.4}$$

Therefore our approach is quite similair to the one found in Brunnemeier *et al* (2008). Which makes our main UIP equation to be as follows:

$$z_{t+1} = (i_A - i_B) - (\Delta s_{t+1})(3.5)$$

The analysis we are to concur is to test whether or not the UIP condition holds in practice, that is

$$E_t[z_{t+1}] = 0 \tag{3.6}$$

3.1 Data interpretation

The data is based on daily spot exchange rates from 2000-2012, base currency is the Euro, the interest rates is a range of 3-month interbank interest rates from G10 countries, all obtained from Bloomberg. We use daily exchange rates quoted at the closing rate. Furthermore the interest rates are obtained at daily value. When analyzing cross country financial markets, the banking days are inconsistent of each other. This is why the data has been 'synchronized'(not interpolated), depending on the analysis, so that the rates at a particular date in one country, also correspond with a quoted rate in the other country. In other words, the mantra is, rather to skip a banking day than to use asynchronous cross-country data. However, even in the worst case, current filtering has 2962 synchronized data points. Assuming 251 trading days on average, the loss of data equals 1.67%, this is not considered significant. For data analysis MatLab and R is used interchangeably.

3.2 The analysis

The first analysis we will conduct, is a simple t-test analysis of the UIP in terms of USD/JPY. Therefore we convert our Euro rates into USD/JPY rates:

$$\frac{1}{E_{EUR/USD}} E_{EUR/JPY} = E_{USD/JPY} \tag{3.7}$$

Now we evaluate the value of z_{t+1} according to the formula stated in 3.4 and the following results occur. Notice figure 3.1, every point different from the green line indicates a point in time t when carry trading was possible. When using the word possible it does not necessarily mean profitable. This is because of the discrepancies in error and different transaction costs.

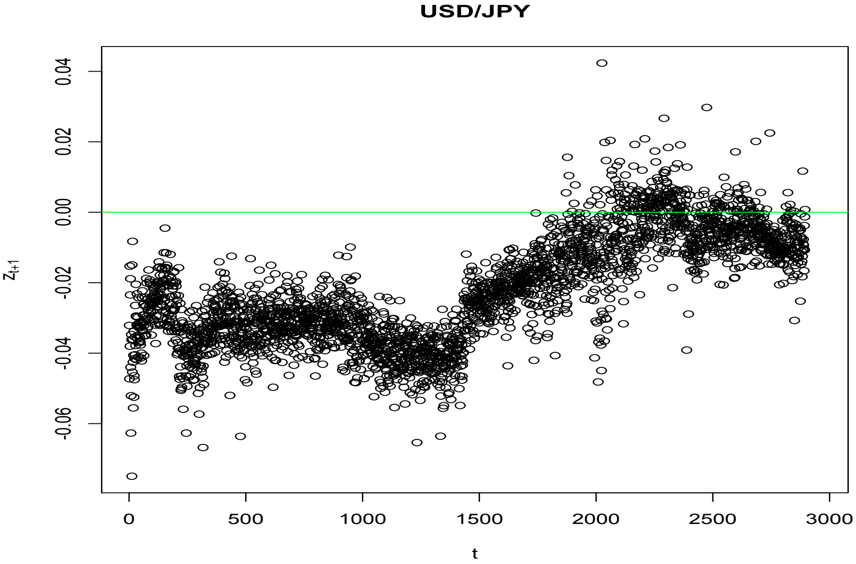


Figure 3.1 z_{t+1}between USD/JPY from 2000-2012

μ	Skew[z_{t+1}]
0.023	0.41

Examining the mean, the average return based on the UIP condition would be 2.3% over the time period. Furthermore looking at the skewness the distribution has a right tail which suggests a higher concentration of values below the mean, thereby closer to the expected value of 0, $E_t[z_{t+1}]$. But this is by far not a very statistically thorough analysis. So let us delve a little deeper to analyze the numbers in greater detail.

3.3 The *t*-test

First the hypothesis test, in this particular test, we are interested in two particular outcomes.

$$H_0 = E_t[z_{t+1}] = 0 \tag{3.8}$$

$$\mu_1 \neq 0 \tag{3.9}$$

Thereby we express our situation by testing on the two above mentioned hypothesis. That is, the null hypothesis, states that the UIP condition holds, the alternative hypothesis is that it does not hold. We will evaluate these criteria on a basic two-sided t test.

```
One Sample t-test

data:  z
t = 61.3584, df = 2960, p-value < 2.2e-16
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 0.02219931 0.02366494
sample estimates:
 mean of x
0.02293213
```

Now if anything before suggested that the expected value of z_{t+1} could be 0, then this t.test clearly says otherwise. Interpreting the results the probability of the null hypothesis $H_0 \leq 0.00000000000000022$. Most statisticians would reject the null hypothesis if the p-value was to be below 0.1, therefore having a value of e-16 highly suggests rejection. Furthermore, we can conclude that the 95% confidence interval, that is, the range in which the data occurs 95% of the time, is very marginal, and notice, non-negative.

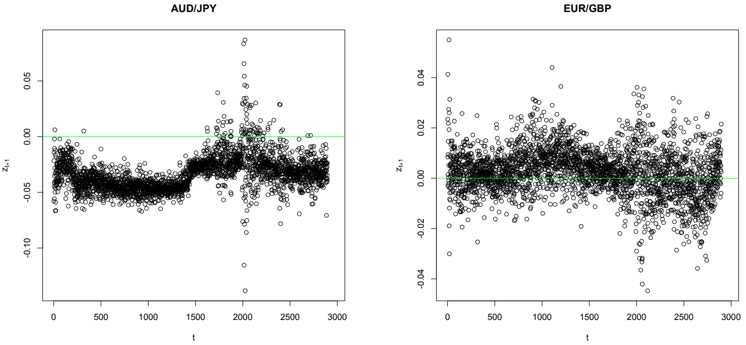
Now this was only for the USD/JPY situation. Let us also try scenarios AUD/JPY, EUR/GBP, EUR/USD, and SEK/NOK. Once again algebraic conversion as before. Multiplying 1/AUD with EUR/JPY to get the AUD/JPY rate, and multiplying 1/SEK with EUR/NOK to get the SEK/NOK rate. Table 3.1 below shows the summary statistics on the data.

Table 3.1 Range of statistics based on UIP analysis.

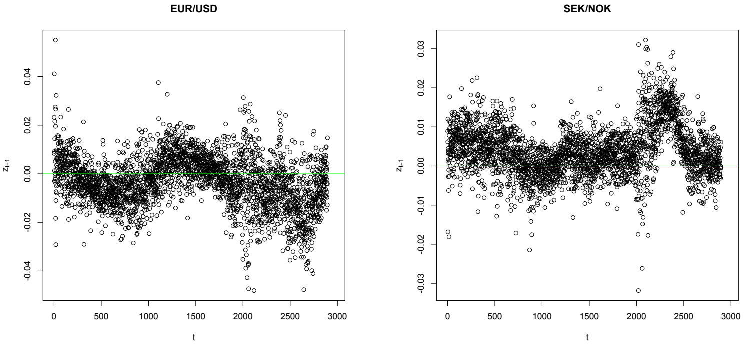
	USD/JPY	**AUD/JPY**	**EUR/GBP**	**EUR/USD**	**SEK/NOK**
μ	.023	.050	-.011	.0013	-.078
Skew$[z_{t+1}]$	.41	.21	0.12	-.30	-5.77
p-value $<$	2.2e-16	2.2e-16	2.2e-16	2.038e-06	2.2e-16
CI	$.022 \leq \mu \leq 024$	$.050 \leq \mu \leq .051$	$-.011 \leq \mu \leq .10$	$.0007 \leq \mu \leq 0018$	$-.079 \leq \mu \leq -.078$

Interestingly enough the t test shows similar p-values for four out of the five currency-crosses. That is, the null-hypothesis that $E_t[z_{t+1}] = 0$ is highly unlikely in four out of the five scenarios. Using table 3.1 together with 3.3 you would be able to conclude similar analysis. The only figure which shows to have any likelihood of confirming the UIP condition is 3.2(c). The green line, as before, is where $z_{t+1} = 0$. Skewness shows mostly mean centered data, except for the SEK/NOK case, where a skewness of -5.77 indicates a high concentration of the distribution mass to be centered to the left of the mean. Comparing with 3.2(d) it is possible to get a rough idea of how the most 'mass' of the distribution is lower than -0.78.

Judging from the results above we should be able to reject the null hypothesis fairly easily, since none of the probabilities have shown to be significant. Not even at $p > 0.1$. Except for the t.test, one highly relevant technique on this matter is a linear regression analysis.



(a) z_{t+1} for AUD/JPY (b) z_{t+1} for EUR/GBP



(c) z_{t+1} for EUR/USD (d) z_{t+1} for SEK/NOK

Figure 3.2 As clearly shown at the plots above, by very rough estimation, only the EUR/USD plot seems to have any possibility of proving $E_t[z_{t+1}] = 0$

3.4 Linear regression analysis

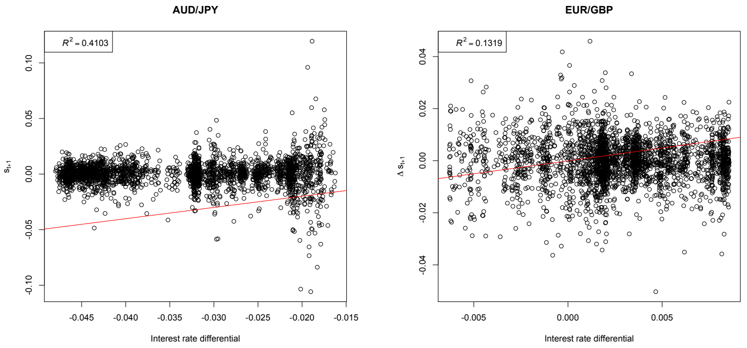
The linear model in question would be a linear model based on our previous formulation of the UIP equation. We have two variables to account for, that is, Δs_{t+1}, which is the exchange rate of depreciation (appreciation), and the interest rate differential, $\Delta i = i_t^* - i_t$. i_t^* being the foreign currency interest rate, funded by the base currency interest rate i_t. We will use a simple linear model.

$$y_t = \alpha + \beta x_t + \epsilon_t \tag{3.10}$$

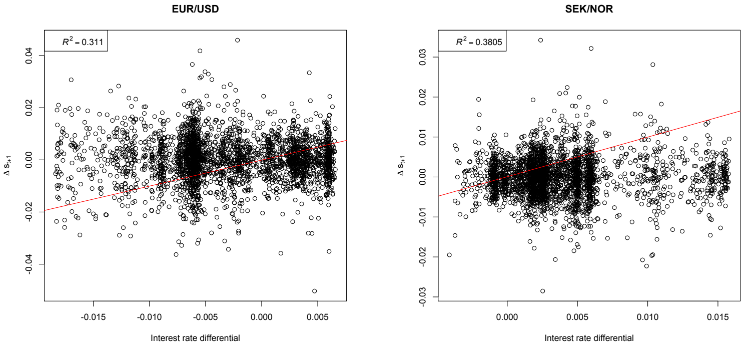
Which will translate into

$$\Delta s_{t+1} = \alpha + \beta \Delta i_t + \epsilon_t \tag{3.11}$$

The variables α, β, and ϵ, translates into the intercept, slope and the random error associated with the model. In UIP terms, α would be an indicator of the risk premium associated with such a trade. β is the weight multiplied on the interest rate spread. For the UIP condition to hold, the value of $\alpha = 0 \wedge \beta = 1$.



(a) Δs_{t+1} , Δi_t for AUD/JPY (b) Δs_{t+1} , Δi_t for EUR/GBP



(c) Δs_{t+1} , Δi_t for EUR/USD (d) Δs_{t+1} , Δi_t for SEK/NOK

Figure 3.3 Figures above are regressions of $\Delta s_{t+1} = \alpha + \beta \Delta i_t + \epsilon_t$

Analyzing figures and the table below give us a series of pointers to some conclusions. First of all, some of these currency crosses are actually fairly close to proving the UIP condition.

But still you would conclude there is a clear violation of the UIP in most cases,

	USD/JPY	**AUD/JPY**	**EUR/GBP**	**EUR/USD**	**SEK/NOK**
α	-.00032	.00033	-5.089e-05	-8.646e-05	7.467e-05
	(.00024)	(.00079)	(2.038e-04)	(1.837e-04)	(1.310e-04)
β	.989	1.013	9.899e-01	9.972e-01	9.905e-01
	(.0093)	(.023)	(4.721e-02)	(2.759e-02)	(2.350e-02)
p-value $<$	2.2e-16	2.2e-16	2.2e-16	2.038e-06	2.2e-16
ρ	.798	.4101	.1316	.3108	.3803
R^2	.7981	.4103	.1319	.311	.3805
Skewness	.229742	1.096157	-.1156916	-.1953176	.3790382

Table 3.2 Statistics based on the regression analysis. In paranthesis the standard error for the variable. Data included from 2000-2012 (July).

even when looking at the long term figures (12 years). Another very important fact, is also to notice that a linear model is not a very good fitting criteria for this type of data, however, we can still get much closer by taking into account the possibility of serial autocorrelation in the data. That is, are the various spot rates and interest rates time dependant? And thereby, the residuals as well. If that is the case, we would not get a correct estimation should we chose not to take this factor into account.

3.5 Serial correlation in FX data

Formally autocorrelation function (ACF) is described as

$$\rho_{XX}(t_1, t_2) = \rho(t_1, t_2) = \frac{\gamma_{XX}(t_1, t_2)}{\sqrt{\sigma^2(t_1)\sigma^2(t_2)}} \tag{3.12}$$

$$\rho_{XX}(\tau) = \frac{_{XX}(\tau)}{\gamma_{XX}(0)} = \frac{\gamma_{XX}(\tau}{\sigma_X^2} \tag{3.13}$$

Where $\sigma_X^2(t)$ is the variance of the process, and $\rho_{XX}(0) = 1$. Before chosing which method is more appropriate, it is relevant to conclude whether the time series is stationary or non-stationary. A stationary process is one which has a mean, and a constant variance. A non-stationary process is one which has neither. That is, looking at one specific time frame $t = [100 : 200]$, does not necessarily reveal any information on any future time frame such as $t = [400 : 500]$. Let us in this case analyze the series USD/JPY. Looking at figure 3.5, it is safe to assume a non-stationary process in this case. Also by simple rational thinking you would rarely consider financial market behaviour to be anything but non-stationary.

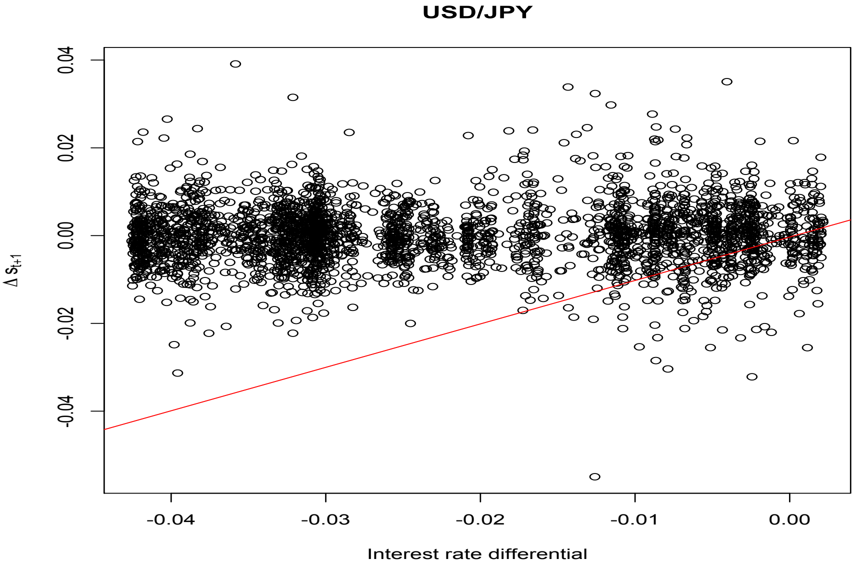


Figure 3.4 Δs_{t+1} , Δi_t for USD/JPY

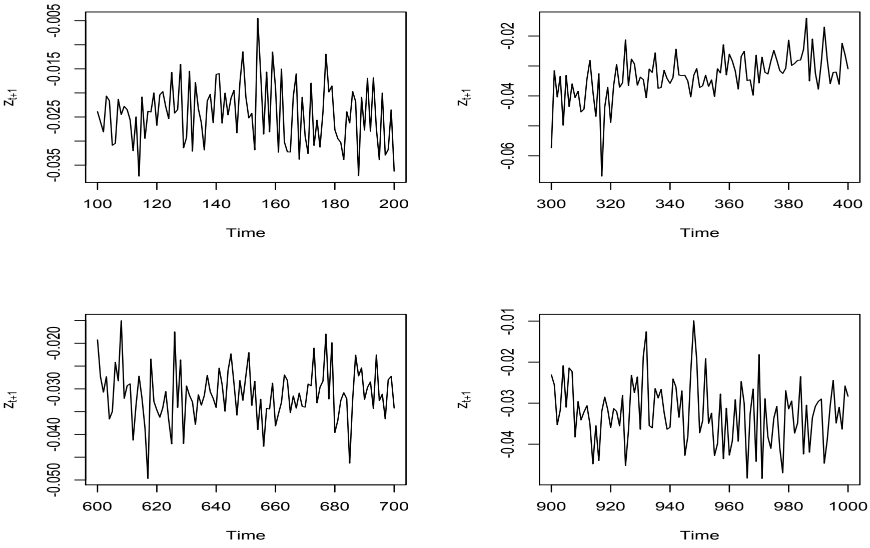


Figure 3.5 Looking at z_{t+1} for USD/JPY in four different time scopes

Having concluded the type of data we will now try to look at the auto-correlation of the data and try to build a model which could prove to be a better fit than the simple linear regression model from 3.2. First we should test for auto correlation. This is done by plotting the auto-correlation function and the partial autocorrelation function. However, before doing so, it is relevant to check to spurious relationships, that is whether or not a linear proportionality exists between the two processes or if it could be a part of the non stationary behaviour of the data. In other words, is the autocorrelation relationship real, or not? As described by Bisgaard and Kulachi (2011), correlation is not always causal. In fact, often you may find correlations between highly unlikely variables. Therefore we must proceed with caution as to conclude whether or not correlations do exist.

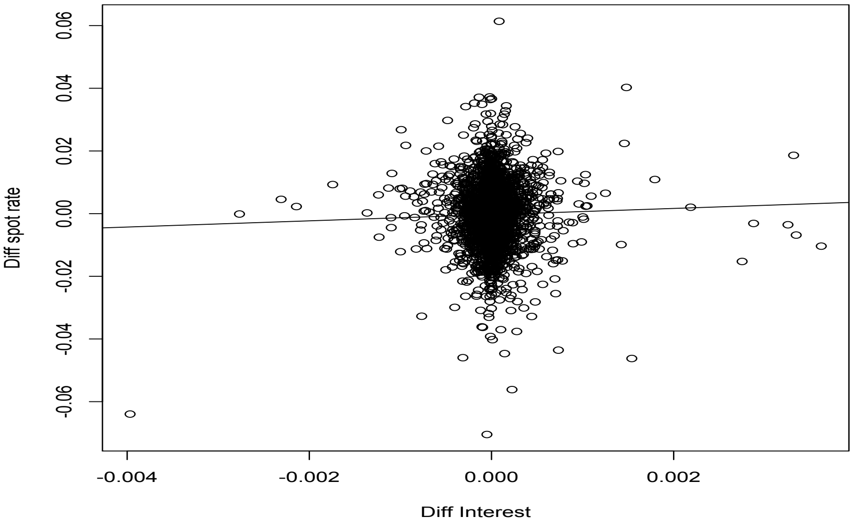


Figure 3.6 Looking at $X_t = \Delta i_{t-1}$ and $Y_t = \Delta s_{t+1t-1}$ for USD/JPY

There exist many possibilities to discover or reject the possibility of correlation. In this thesis I will focus on only a few of them. Figure 3.6 shows the relationship between the first difference between the residuals. If we are to conclude a correlation, the linear proportionality which existed before taking the first difference, should also exist when doing so. Even though the relationship might be weak, there is still a linear relationship between the two variables.

Another statistic which could be used to suggest autocorrelation is the Durbin-Watson statistic. The Durbin-Watson test is a rather peculiar number since its range is from 0-4, and some of the intervals are 'grey-zone' indicators, which means that you cannot really conclude much should you happen to have a number within this range.

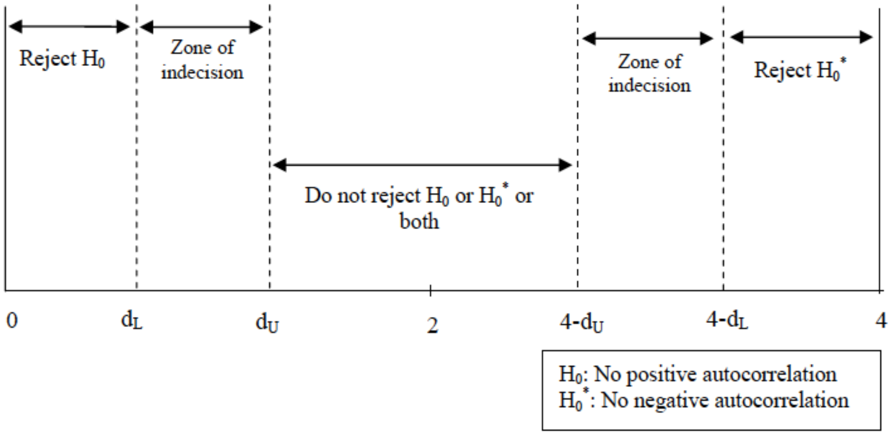

Reject H0
Zone of indecision
Do not reject H0 or H0* or both
Zone of indecision
Reject H0*
0
dL
dU
2
4-dU
4-dL
4
H0: No positive autocorrelation
H0*: No negative autocorrelation

Figure 3.7 Durbin-Watson indicator overview

Now, calculating the DW statistic on our USD/JPY linear model, $z_{t+1} = (i_A - i_B) - (\Delta s_{t+1})$. We get $DW_{USD/JPY} = 0.0013$. Interpreting this result solely on the DW basis, you would say that the data is negatively autocorrelated. Which is similar to negative proportionality, if the output (Y_t) rises, the input (X_t) would fall. Based on the plot in 3.6 and the Durbin-Watson test, I will conclude that there exists an autocorrelated relationship. It may not be perfectly accurate, or indeed clean from possibilities spurious relationships, but I will continue the analysis.

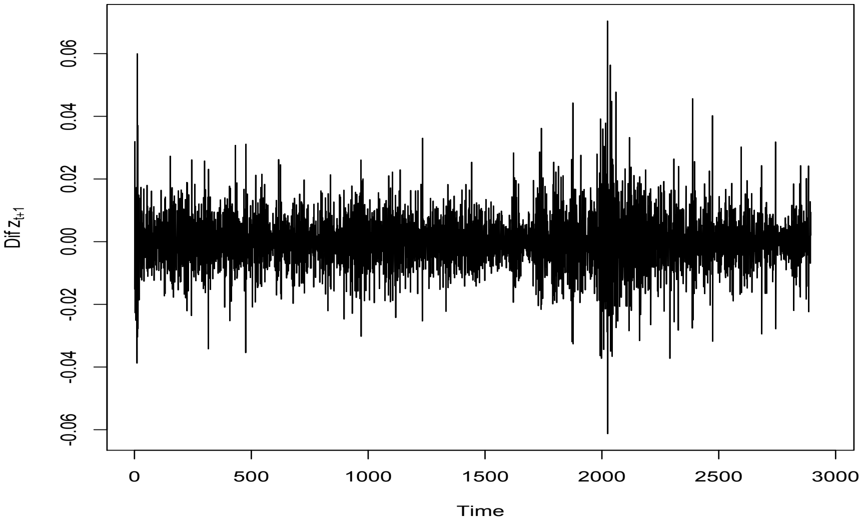


Figure 3.8 First difference of z_{t+1}

Next we will look at the ACF and the partial autocorrelated functions (PACF), to look at how the autocorrelated lags are distributed. By determining the appropriate lag between the variables, we are able to get closer to a more appropriately fitting model. Remember we stated that the data was non-stationary. In order for the data to be approximated with auto regressive (AR) models we will transform the data to be stationary by taking the first difference $\Delta_t - 1$ to z. This is done since the world decomposition theorem allows any stationary process to be approximated by AR models.

Looking at the diagrams in 3.9 we see that there certainly is an autocorrelation. Mostly at lag 0 and lag 1, but in fact going all the way until ≈ 15. The covariance plot in the bottom also shows a slight pattern in the correlations, showing what is a small sine-curve. Judging on these diagrams it could be appropriate to fit an AR(15) model to the data in order to get rid of the lags. Thereby we will have a model which consists of

$$\tilde{x}_t = \phi_1\tilde{x}_{t-1} + \phi_2\tilde{x}_{t-2} + \phi_3\tilde{x}_{t-2} + +\phi_4\tilde{x}_{t-4} + \phi_5\tilde{x}_{t-5} + ... \tag{3.14}$$

$$+\phi_6\tilde{x}_{t-6} + \phi_7\tilde{x}_{t-7} + \phi_8\tilde{x}_{t-8} + \phi_9\tilde{x}_{t-9} + \phi_{10} + \tilde{x}_{t-10} + ... \tag{3.15}$$

$$+\phi_{11}\tilde{x}_{t-11} + \phi_{12}\tilde{x}_{t-12} + \phi_{13}\tilde{x}_{t-13} + \phi_{14}\tilde{x}_{t-14} + \phi_{15}\tilde{x}_{t-15} \tag{3.16}$$

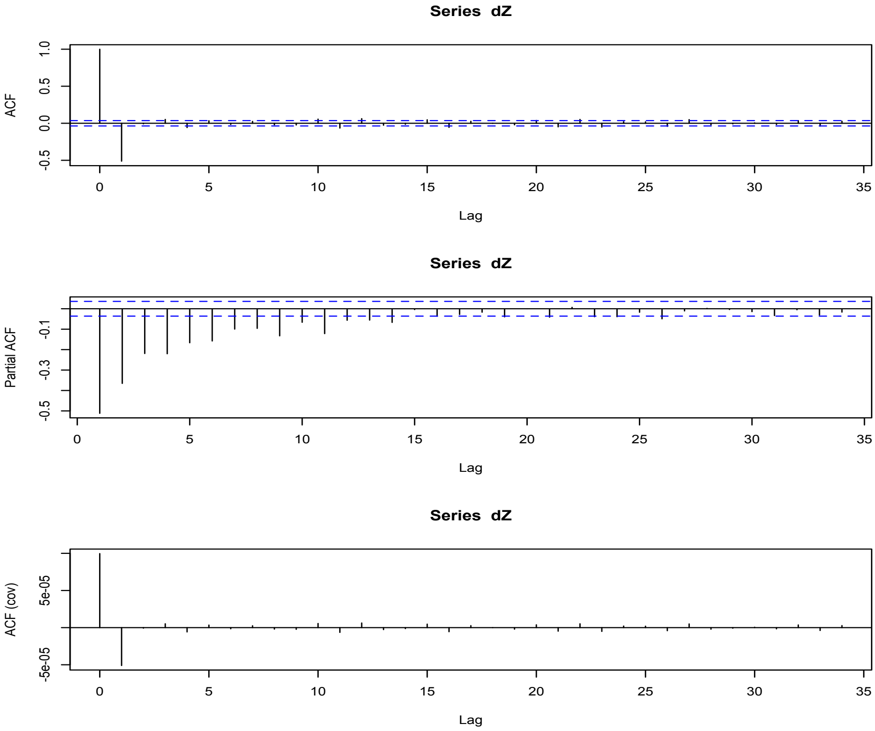


Figure 3.9 Top to bottom, ACF, PACF and ACF(Covariance)

Now, this does look very inconvenient, and it certainly is. But you would remove any insignificant factors following the calculation of the coefficients to make the function cleaner.

```
Call:
arima(x = x.in, order = c(15,0,0), na.action = na.pass), include.mean = F, method = "ML")

Coefficients:
          ar1      ar2     ar3      ar4     ar5     ar6     ar7      ar8      ar9    ar10
      -0.0455  -0.0247  0.0188  -0.0404  0.0100  0.0002  0.0159  -0.0169  -0.0101  0.0441
s.e.   0.0277   0.0273  0.0267   0.0256  0.0253  0.0245  0.0238   0.0229   0.0226  0.0222
```

```
         ar11     ar12     ar13     ar14     ar15
      -0.0078   0.0591   0.0062   0.0115   0.0288
s.e.   0.0214   0.0211   0.0204   0.0201   0.0198

sigma^2 estimated as 5.055e-05:  log likelihood = 10207.05,  aic = -20380.11
```

Term	Estimated coefficient	Standard error	t-Ratio
$\hat{\phi}_1$	-0.0455	0.0277	-1.642599278
$\hat{\phi}_2$	-0.0247	0.0273	-0.904761905)
$\hat{\phi}_3$	0.0188	0.0267	0.704119850
$\hat{\phi}_4$	-0.0404	0.0256	-1.578125000
$\hat{\phi}_5$	0.0100	0.0253	0.395256917
$\hat{\phi}_6$	0.0002	0.0245	0.008163265
$\hat{\phi}_7$	0.0159	0.0238	0.668067227
$\hat{\phi}_8$	-0.0169	0.0229	-0.737991266
$\hat{\phi}_9$	-0.0101	0.0226	-0.446902655
$\hat{\phi}_{10}$	0.0441	0.0222	1.986486486
$\hat{\phi}_{11}$	-0.0078	0.0214	-0.3644860
$\hat{\phi}_{12}$	0.0591	0.0211	2.8009479
$\hat{\phi}_{13}$	0.0062	0.0204	0.3039216
$\hat{\phi}_{14}$	0.0115	0.0201	0.5721393
$\hat{\phi}_{15}$	0.0288	0.0198	1.4545455

Table 3.3 AR(15) coefficients and statistics, based on USD/JPY.

Because of the primary focus of this thesis, further analysis on the UIP shall not be made. However, the point of autocorrelation is clear, and would have been possible to elaborate on further by concurring more investigation into the matter. Just to give an impression on the fit of the model, even without further 'cleaning' of the model, we can see that our model fits pretty well into the picture after the AR-fit. Top to bottom the residuals show little to no lag except for time 0. The Ljung-Box statistic plot shows with a very high p-value that the data can be interpreted as independant, which means our model is a good fit.

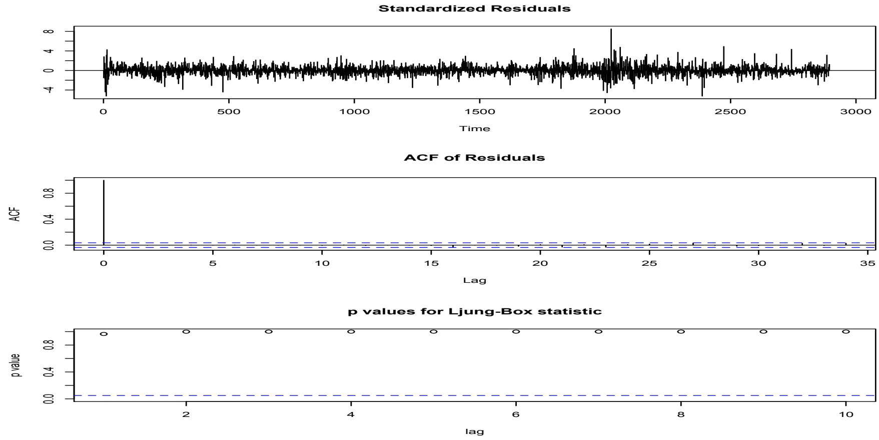


Figure 3.10 Top to bottom, AR(15) fit to residuals, ACF of residuals, and Ljung-Box statistic.

3.6 VIX & the TED

Having looked into the possibilities of carry trading and the violation of the uncovered interest parity, we will now look into factors which could show to prove interesting when analyzing the cause and the effect of the foreign exchange market. The VIX index is the volatility index of the SP500. The index is widely known for its highly indicative properties. Being an option listed on the Chicago Board of Options Exchange (CBOE), its price reflects the 'mood' of financial actors in e.g. the foreign exchange market. The VIX fluctuations represent the risk-appetite in the market, and therefore it can prove to be a fairly good indicator of whether or not the trend is upward or downward. Collin-Dufresne, Goldstein, and Martin (2001).

Furthermore the TED-spread also has the possibility to show a trend in the markets. Being the spread between the (3 month) U.S treasury bond and the London Interbank interest rate (LIBOR). Looking at figures 3.11 and **??**, it is clear that there is a reaction in both of the indicators on the performance of the market. Index 2000 being the year of 2008, when many banks went bankrupt and the market went bullish, you clearly see how the patterns are evolving.

Now it could be interesting to see how long of a lag would be appropriate in either of the variables in terms of the market. Determining the lag we would then have some basis on evaluating entry/re-entry conditions for conducting trades in the market. Therefore one of the things which is interesting first of all to conclude, is to how big of a lag each of the different currency pairs are inducing. Basically we are conducting similar analysis as the one made in 3.2

under the UIP analysis in order to determine an appropriate lag for each of the currency pairs, except instead of autogression in one variable, we are cross-correlating the VIX/TED with a currency pair. Formally this is represented as

$$\rho_{XY}(t_1, t_2) = \rho(t_1, t_2) = \frac{\gamma_{XY}(t_1, t_2)}{\sqrt{\sigma_X^2 t_1, \sigma_Y^2 t_2}}$$

EUR /	USD	JPY	GBP	CHF	AUD	CAD	SEK	NOK	NZD
VIX	+17	-9	-28	-9	-14(+9)	+8	+25	-17	+10
TED	-10	-8	0	-10	-11	-25	-18	-1	0

Table 3.4 Lags determined by examination of cross-correlation by and a currency pair. See Apendix for plots

Judging from the table above, and from the figures in the appendix, it is quite difficult to use these models as a proxy for prediction. There are many error-possibilities, and far less probabilities of absolute certain estimates. One of the suspicions is that the data is not only auto-correlated, but it is also co-integrated. Having co-integrated data means that you have an underlying third parameter, which is not immediately apparent.

Indeed this is highly likely, since most (macro-)economic data is co-integrated Hendry Juselius (1999). This is intuitively reasoning since some economic data have an almost infinite amount of dependant variables.

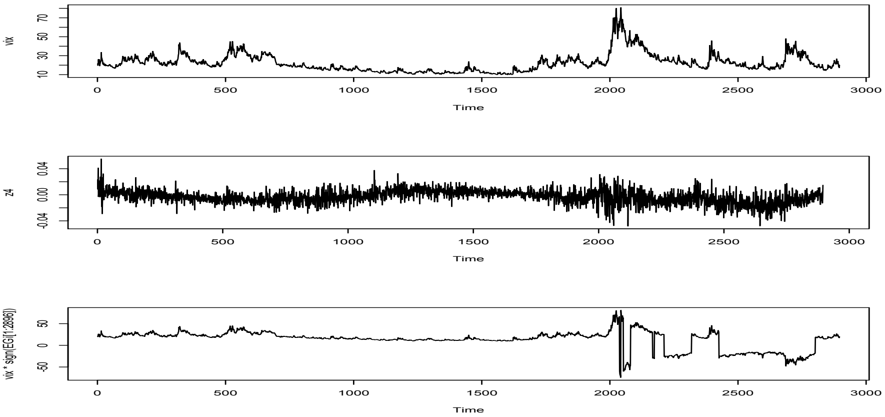


Figure 3.11 The VIX index, return on EUR/GBP carry, $VIX * sign(\Delta_{it-1})$

CHAPTER 4

Portfolio simulation

Based on the previous analysis and explanations, chapter 4 is devoted to practical hands-on analysis of the implementation of the carry trade strategy. In order to do this properly I will use a certain framework by Westergaard Bundsgaard (2012), which is built in MatLab. The framework itself is built to support naive carry trading simulation. In order to test the trading strategies I have modified the framework to suit the testing purposes.

4.1 The Evaluator

Understanding the discrepancies, and the steps performed by the algorithm is important when analysing the results. In effect I will go through the major steps of how the algorithm calculates the profit on the G10 carry strategy.

```
function [profit,span,profits] = evaluateCarry(revInterval,longShortDist,...
    longDist,shortDist,rebalance,STRmethod)
```

evaluateCarry is the main function we execute to calculate the profit. In terms of argument it is dependant on getting information on the revision interval, that is, how often it should check on better forward contracts. The minimum value of this variable is 5 (once a week). longShortDist is the overall distribution between the long and the short positions. This can be translated into a more absolute sense of money distribution in a portfolio. How much money are you willing to invest in long positions, and how much are you willing to put in short positions. The *longDist* and *shortDist* variables represent a distribution between each of the 3 short/long positions. Rebalance is a boolean variable that allows (or forbids) to shift funds from long positions into short positions, and long/short positions in between. STRmethod is the Stop-loss, Take profit, and Re-entry method. This is where the implementation and test of other indicators will be made.

I will evaluate and compare the results on the arguments

```
[profit,span,profits] = evaluateCarry(5,0.5,[1 1 1]/3,[1 1 1]/3,1,STRMethod);
```

Calculation of profit The profit is calculated on a relative basis. Instead of a very common accumulated profit percentage, which does not take into account the relative gain/loss in time, this function calculates profit on a day-by-day relative basis. The final result is the sum of the relative profits.

Interpretation of forward contracts The way the forward contracts are being utilized in the program is by having fixed 90-day contracts. Furthermore if you cancel out a contract by buying the opposite at day 30, the contract you are buying will be a 60-day contract. In other words, the contract length is iterated until it reaches the 90th day, then the contract length is reset and the pattern is repeated.

Checks and build The function is very thorough in checking and double checking conditions of trade, and the conditions of sale. But there is no included transaction costs or other unexpected costs which may be the case in a real world example.

4.1.1 Simple Moving Averages

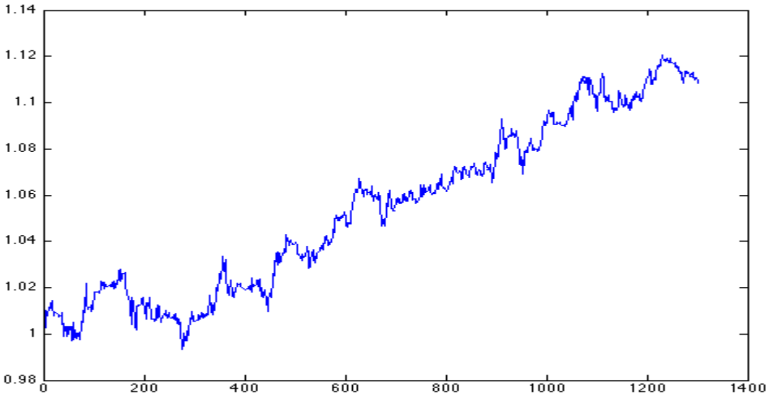


Figure 4.1 Carry trade profits, MA(10),MA(3) strategy. 11% profit

Clean and safe bet, the SMA give an estimated 13% profit at the end of the term. The MA process is modelled by a 10-day and a 3-day average. Trades has been conducted so that whenever the $MA(10) > MA(3)$ =Long investments and whenever the $MA(3) < MA(10)$ =Short investments. The moving average parameters are not fixed, they are merely indicators for the trader. Therefore let us double the parameters and look at the profits again.

Examining the results form the MA(20),MA(6) proces, the results are very similar and almost identical. More exact on the conclusion.

4.1.2 MACD

Using the MACD indicator as the sole strategy for entry exit gives you an estimated profit of 25%. The entry exit conditions are very classical MACD.

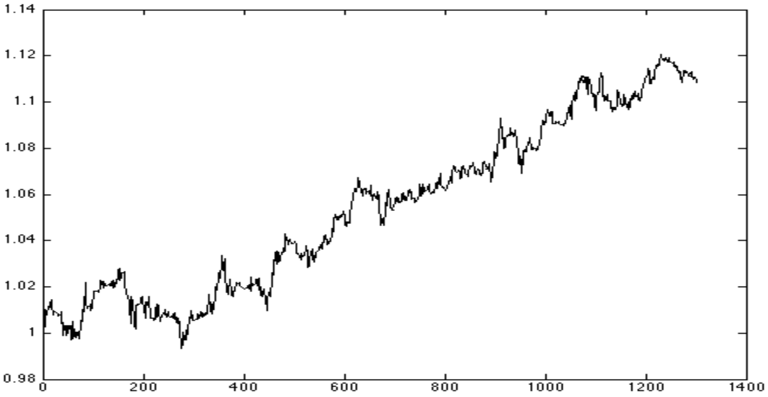


Figure 4.2 Carry trade profits, MA(20),MA(3) strategy. 11% profit

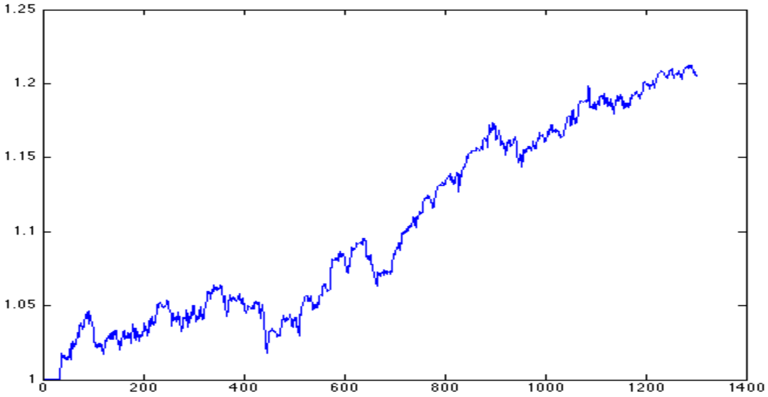


Figure 4.3 Carry trade profits, MACD strategy. 25% profit

We have a solid line following consisting of the difference between the EMA(26) and the EMA(12). There is a dashed lines which is also referred to as the signal indicator. It follows an EMA(6), based on the solid line. Whenever the solid line passes the dashed, were going long, whenever it is below the dashed line, we are shorting.

4.1.3 RoC

Not a very good proxy, however it does measure the acceleration of the market fairly good. In this case we instructed the algorithm to go long when the *RoC* >Price of spot rate, in the same way we are shorting whenever the *RoC* <Price of spot rate. A very simple indicator, it is clearly not advisable to trade solely on its signals.

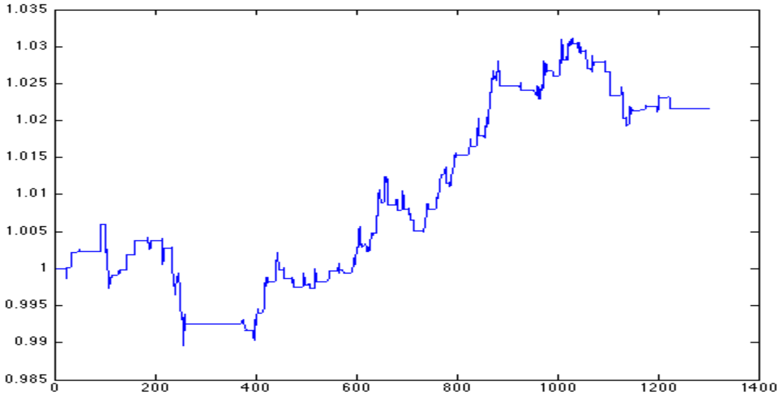


Figure 4.4 Carry trade profits, RoC strategy. 1.2% profit

4.1.4 RSI

Using the RSI can prove to be a very strong indicator of bear/bull-trends in the market. However, it is also something which is highly dependant on the individual traders skill to set some reasonable boundary values. In our case we shall try with lower boundary 35 and upper boundary 65. In other words, we will allow long positions on RSI values 65 and above, and we will disallow long positions (go short) on RSI values 35 and below.

The RSI does not give us the best result, compared to some of the other indicators. Let us try the RSI in relation to price and not boundary values we invent ourselves. This also clearly gives a much higher estimate

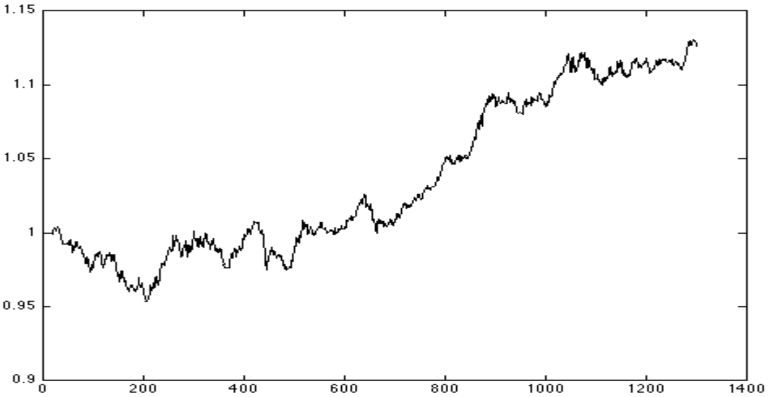


Figure 4.5 Carry trade profits, RSI strategy, 35:65 boundary . 13% profit

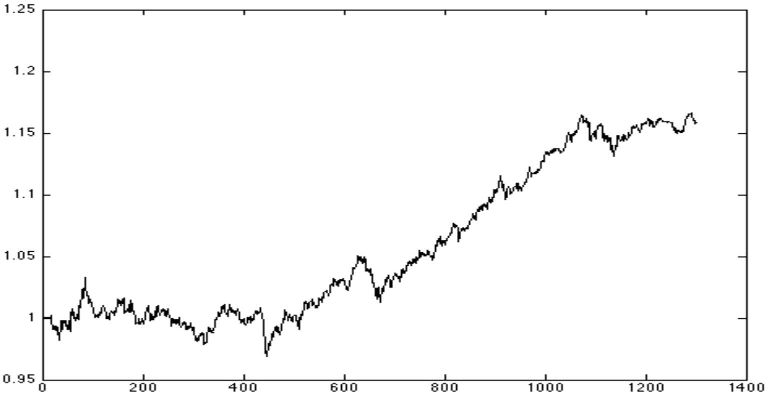


Figure 4.6 Carry trade profits, RSI strategy, RSI < Price . 13% profit

CHAPTER 5

Conclusion

Over all the analysis of the FX market has been very giving. It has been very interesting to see the way the movement of the market is behaving. In terms of our conclusion there are some discrepancies which do have an impact on the final results. First of all, even though we try our best to mimic the real life fx market in the algorithm and the data, there are errors and circumstances which are clearly not accounted for. One of which is the assumption of complete market rationality, that all actors in the market make rationally valid decisions in their behavior. Furthermore sentiment is not reflected in the analysis, something which recently has gotten a great popularity even for the retail investor. You could argue that this information is present in the price quotas, but there may also be discrepancies between even listed prices on securities

Never the less, it is safe to say that the carry trade strategy works. In fact it has a possibility of return even with the usage of the SMA. **??** represents the result gathered from the usage of the technical indicators and the profitability thereof.

	MA(10,3)	MA(20,6)	MACD	RoC	RSI(35,65)	RSI(Rate)
profit	1.1070	1.1100	1.2084	1.0216	1.1580	1.1259

Table 5.1 Accumulated relative profits by using the different technical indicators. Quoted as $(1 + r)$.

It is clear that we have not gotten ’to the bottom’ of this. By far, the analysis could continue into a further great amount of detail. The most important ideas to gather from this project is that carry trade does in fact exist and in many cases work. Technical indicators on trading decisions are indeed valid trend predictors. And the UIP condition does not seem to hold in its essence. This is mostly because of the approximation used, where the true expected future value of the spot rate is approximated to the exact future value. The discrepancy in between is what makes carry trade profitable, Chinn Frankel (2002).

Appendix A

Stuff

A.1 R code

```
DATA <- read.csv("/Users/Maxim/Dropbox/Private/Bachelor_Uddannelsen/ \\
Bachelor_thesis/DataBloomberg_00-12complete_\\ ... cleanSpotRatesFINAL.csv", header = TRUE, sep =",", quote = "\"",\\ dec = ".")
PPPeur <-read.csv("/Users/Maxim/Dropbox/Private/Bachelor_Uddannelsen/\\
... Bachelor_thesis/Consumerprices ECB 2000-2012jul.csv",\\
... header = TRUE, sep =",", quote = "\"", dec = ".")

library(e1071)

%d%m%Y
########################################
# z1
#### USD/JPY
x11(width=10, height=6)
UJi=((log(DATA[1:2961,5]))-(log(DATA[1:2961,3])))/100
UJs=diff(log((1/DATA[1:2962,6]*DATA[1:2962,4])),1)
z1=UJi-UJs
plot(z1,main=’USD/JPY’,ylab=expression(’z’[t+1]),xlab=’t’)+abline(h=0,col=’green’)
lmf1=lm(z1~UJi-UJs)
lmr1=resid(lmf1)
###PLOTS#
summary(lmf1)
plot(UJs~UJi,main=’USD/JPY’,xlab=’Interest rate differential’,ylab=expression(Delta~"s"[t+1]))+abline(lmf1,col=’red’)
legend("topleft", legend = ~italic(R^2) == 0.7981)
par( mfrow = c( 3, 1 ) )
ts1 = ts(z1[100:200],start=100)
ts2 = ts(z1[300:400],start=300)
ts3 = ts(z1[600:700],start=600)
ts4 = ts(z1[900:1000],start=900)
ts.plot(ts1,ylab=expression("z"[t+1]))+
ts.plot(ts2,ylab=expression("z"[t+1]))+
ts.plot(ts3,ylab=expression("z"[t+1]))+
ts.plot(ts4,ylab=expression("z"[t+1]))
help(ts.plot)

#########################################
# z2
#### AUD/JPY
```

```
AJi=((log(DATA[1:2961,5]))-(log(DATA[1:2961,11])))/100
AJs=diff(log((1/DATA[1:2962,12]*DATA[1:2962,6])),1)
z2=AJi-AJs
x11(width=15, height=6)
plot(z2,main=’AUD/JPY’,ylab=expression(’z’[t+1]),xlab=’t’)+
abline(h=0,col=’green’)
lmf2=lm(z2~AJi-AJs)
lmr2=resid(lmf)
###PLOTS#
summary(lmf2)
plot(AJs~AJi,main=’AUD/JPY’,xlab=’Interest rate differential’,ylab=expression("s"[t+1]))+abline(lmf2,col=’red’)
legend("topleft", legend = ~italic(R^2) == 0.4103)
#par( mfrow = c( 2, 3 ) )
########################################
# z3 ### FEJL FEJL FEJL MANGLER LOG
#### EUR/GBP
EGi=((log(DATA[1:2961,7]))-(log(DATA[1:2961,2])))/100
EGs=diff(log(DATA[1:2962,4]),1)
z3 = EGi-EGs
lmf3=lm(z3~EGi-EGs)
lmr3=resid(lmf3)
plot(z3,main=’EUR/GBP’,ylab=expression(’z’[t+1]),xlab=’t’)+
abline(h=0,col=’green’)
###PLOTS#
summary(lmf3)
plot(EGs~EGi,main=’EUR/GBP’,xlab=’Interest rate differential’,ylab=expression(Delta~"s"[t+1]))+
abline(lmf3,col=’red’)
legend("topleft", legend = ~italic(R^2) == 0.1319)
#par( mfrow = c( 2, 3 ) )

########################################
# z4 ### FEJL FEJL FEJL MANGLER LOG
#### EUR/USD
#z4
EUi=((log(DATA[1:2961,3]))-(log(DATA[1:2961,2])))/100
EUs=diff(log(DATA[1:2962,4]),1)
z4 = EUi-EUs
lmf4=lm(z4~EUi-EUs)
lmr4=resid(lmf4)
plot(z4,main=’EUR/USD’,ylab=expression(’z’[t+1]),xlab=’t’)+
abline(h=0,col=’green’)
###PLOTS#
summary(lmf4)
plot(EUs~EUi,main=’EUR/USD’,xlab=’Interest rate differential’,ylab=expression(Delta~"s"[t+1]))+
abline(lmf4,col=’red’)
legend("topleft", legend = ~italic(R^2) == 0.311)

########################################
# z5
#### SEK/NOK
z5 = ((DATA[1:2961,14])/100-(DATA[1:2961,16]/100))-diff(log((1/DATA[1:2962,16]*DATA[1:2962,18])),1)
plot(z5,xlab=’t’,ylab=’z’)+abline(h=0, col = "green")

#
SNi=((log(DATA[1:2961,17]))-(log(DATA[1:2961,15])))/100
SNs=diff(log((1/DATA[1:2962,16]*DATA[1:2962,18])),1)
z5 = SNi-SNs
plot(z5,main=’SEK/NOK’,ylab=expression(’z’[t+1]),xlab=’t’)+
abline(h=0,col=’green’)
lmf5=lm(z5~SNi-SNs)
lmr5=resid(lmf5)
###PLOTS#
summary(lmf5)
plot(SNs~SNi,main=’SEK/NOR’,xlab=’Interest rate differential’,ylab=expression(Delta~"s"[t+1]))+
abline(lmf5,col=’red’)
legend("topleft", legend = ~italic(R^2) == 0.3805)

########################################
## ANALYSIS OF VARIANCE & Skewness
########################################
anova(lmf1)
anova(lmf2)
anova(lmf3)
anova(lmf4)
anova(lmf5)
#Skewness
skewness(z1,na.rm=TRUE,type=3)
skewness(z2,na.rm=TRUE,type=3)
skewness(z3,na.rm=TRUE,type=3)
skewness(z4,na.rm=TRUE,type=3)
skewness(z5,na.rm=TRUE,type=3)

#######################################
# ANALYSIS OF AUTOCORRELATION
#######################################
# USD/JPY
###########
```

```
plot(diff(UJi,1),diff(UJs,1),xlab=’Diff Interest’,ylab=’Diff spot rate’)
#lmf1t=lm(diff(z1,1)~diff(UJi,1)-diff(UJs,1))
abline(lmf1)
dw.test(z1)
dZ=diff(z1,1)
acf(dZ,na.action=na.pass)
pacf(dZ,na.action=na.pass)
acf(dZ,na.action=na.pass,type=c(’covariance’))
dZar<-arima.plot(dZ,15,0,1,0,0,0,T)
tsdiag(dZar)

### VIX ANALYSIS
vix=DATA[,21]
ted=DATA[,23]
x11(width=10,height=7)
layout(matrix(c(1,1,2,3),2,2,byrow=TRUE))
par( mfrow = c( 3, 1 ) )

 ts.plot(vix)
 ts.plot(z4)
 ts.plot(vix*sign(EGi[1:2896]))

ts.plot(vix[1:2895]*sign(diff(EGi[1:2896],1)))

 ts.plot(ted)
 ts.plot(z4)
 ts.plot(ted*sign(EGi[1:2896]))

##data(USeconomic)
#x <- ts.union(log(M1), log(GNP), rs, rl)
#m.ar <- ar(x, method = "ols", order.max = 5)
#y <- predict(m.ar, x, n.ahead = 200, se.fit = FALSE)
#seqplot.ts(x, y)
x=log(vix)
y=log(ted)
ts.plot(x,type=’l’)
lines(y,col=’red’)

##### Determining lag of VIX & TED on the currency pairs
par( mfrow = c( 3, 3 ),main=’CCF’)
ccf(diff(vix,1),diff(log(DATA[,3]),1),na.action=na.pass) #USD Most significant +17
ccf(diff(vix,1),diff(log(DATA[,5]),1),na.action=na.pass) # JPY -9
ccf(diff(vix,1),diff(log(DATA[,7]),1),na.action=na.pass) #GBP -28
ccf(diff(vix,1),diff(log(DATA[,9]),1),na.action=na.pass) #CHF -9
ccf(diff(vix,1),diff(log(DATA[,11]),1),na.action=na.pass) #AUD -14 (+9)
ccf(diff(vix,1),diff(log(DATA[,13]),1),na.action=na.pass) #CAD +8
ccf(diff(vix,1),diff(log(DATA[,15]),1),na.action=na.pass) #SEK +25
ccf(diff(vix,1),diff(log(DATA[,17]),1),na.action=na.pass) #NOK -17
ccf(diff(vix[734:2894],1),diff(log(DATA[734:2894,19]),1),na.action=na.pass) #NZD +10(-27) (Data from index >734)

par( mfrow = c( 3, 3 ),main=’CCF’)
ccf(diff(ted,1),diff(log(DATA[,3]),1),na.action=na.pass) #USD -10
ccf(diff(ted,1),diff(log(DATA[,5]),1),na.action=na.pass) #JPY -8
ccf(diff(ted,1),diff(log(DATA[,7]),1),na.action=na.pass) #GBP 0
ccf(diff(ted,1),diff(log(DATA[,9]),1),na.action=na.pass) #CHF -10
ccf(diff(ted,1),diff(log(DATA[,11]),1),na.action=na.pass) #AUD -11
ccf(diff(ted,1),diff(log(DATA[,13]),1),na.action=na.pass) #CAD ~-25(-21,+13)
ccf(diff(ted,1),diff(log(DATA[,15]),1),na.action=na.pass) #SEK -18
ccf(diff(ted,1),diff(log(DATA[,17]),1),na.action=na.pass) #NOK -1
ccf(diff(ted[734:2894],1),diff(log(DATA[734:2894,19]),1),na.action=na.pass) #NZD 0

UVA<-arima(vix,order=c(20,1,0))
JVA<-arima(vix,order=c(20,1,0))
GVA<-arima(vix,order=c(20,1,0)) #Based on pacf(vix)
CVA<-arima(vix,order=c(20,1,0))
AVA<-arima(vix,order=c(20,1,0))
CVA<-arima(vix,order=c(20,1,0))
SVA<-arima(vix,order=c(20,1,0))
NVA<-arima(vix,order=c(20,1,0))
NZVA<-arima(vix,order=c(20,1,0))

UTA<-arima(ted,order=c(20,1,0))
JTA<-arima(ted,order=c(20,1,0))
GTA<-arima(ted,order=c(20,1,0)) #Based on pacf(vix)
CTA<-arima(ted,order=c(20,1,0))
ATA<-arima(ted,order=c(20,1,0))
CTA<-arima(ted,order=c(20,1,0))
STA<-arima(ted,order=c(20,1,0))
NTA<-arima(ted,order=c(20,1,0))
NZTA<-arima(ted,order=c(20,1,0))

EUR USD Spotrate JPY Spotrate GBP Spotrate CHF Spotrate AUD Spotrate CAD Spotrate SEK Spotrate NOK Spotrate NZD Spotrate VIX 3mnthTbill
TED D12EURUSD MOVG UIP (EURUSD)
ccf(ted,EUs,na.action=na.pass)

ff<-arima(dZ,c(15,0,1))
```

```
plot(ff)
fitt<-dZ-ff$residuals
plot(fitt)
LMF<-lm(fitt~z1)
length(fitt)

plot(DATA[1:120,3],type='l',ylab='EUR/USD')
movg1<-rollmean(DATA[,3],100)
movg2<-rollmean(DATA[,3],30)
lines(movg1,col='red')
lines(movg2,col='green')
library(TTR)
lines(diff(EMA(DATA[1:120,3],9),EMA(DATA[1:120,3],5)),col='green')
E1=EMA(DATA[1:120,3],12)
E2=EMA(DATA[1:120,3],26)
Ed=E1-E2
lines(Ed,col='green')
par( mfrow = c( 2, 1 ) )
plot(DATA[1:120,3],ylab='EUR/USD',type='l')
plot(Ed,type='l',ylab='MACD',col='blue')
lines(EMA(Ed,9),type='p',col='red',lwd=0.2)
```

A.2 MatLab code adjustments

```
function [longOK,shortOK] = STREval(mavg,STRmethod,day)
global macdvec prc nineperma;
% Stop Loss

if STRmethod{1} == 1 %  Simple Moving Average strategy LEAD & LAG
    lead = STRmethod{2}(1);
    lag = STRmethod{2}(2);
    longOK = [mavg(day,:,lead) >= mavg(day,:,lag) false];
    shortOK = [mavg(day,:,lag) <= mavg(day,:,lead) false];
elseif STRmethod{1} == 2 %MACD strategy - Lead Lag non-variable
    lead = 1; %STRmethod{2}(1);
    lag = 1; %STRmethod{2}(2);
    %EMA1 = tsmovavg(mavg, 'e', lead,2)
    %EMA2 = tsmovavg(mavg, 'e', lag,2)
    longOK = [macdvec(day,:,lead) >= nineperma(day,:,lag) false];
    shortOK = [macdvec(day,:,lead) <= nineperma(day,:,lag) false];

elseif STRmethod{1} == 3 %Price Rate of Change
    lead = 1% STRmethod{2}(1); Defined in createMovAv.m at 7-days
    lag = 1% %STRmethod{2}(2);
    longOK = [prc(day,:,lead) >= mavg(day,:,lag) false];
    shortOK = [mavg(day,:,lag) <= prc(day,:,lead) false];
elseif STRmethod{1} == 4
    for i=1:9
    rsi(:,i)=rsindex(mavg(:,i,1));
    end
    %rsi = rsindex(mavg);
    lead = 1;% STRmethod{2}(1); Defined in createMovAv.m at 7-days
    lag = 1;% %STRmethod{2}(2);
    longOK = [rsi(day,:) >= mavg(day,:,lag) false];
    shortOK = [mavg(day,:,lag) <= rsi(day,:) false];
elseif STRmethod{1} == 5
    for i=1:9
    rsi(:,i)=rsindex(mavg(:,i,1));
    end
    %rsi = rsindex(mavg);
    lead = 1;% STRmethod{2}(1); Defined in createMovAv.m at 7-days
    lag = 1;% %STRmethod{2}(2);
    longOK = [rsi(day,:) >= 65 false];
    shortOK = [35 <= rsi(day,:) false];

end
end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [mavg,macdvec,nineperma,prc] = createMovAvg(Ask,n)
L = size(Ask,1);
mavg = zeros(L,9,n);
mavg(:,:,1) = Ask(:,1:9);
for i = 2:n
    for j = 1:L
        mavg(j,:,i) = mean(Ask(max(1,j-i+1):j,1:9),1);
    end

end

[macdvec,nineperma]=macd(mavg);
prc = prcroc(mavg,7);

for i=1:9
   rsi(:,i)=rsindex(mavg(:,i,1));
 end


end
```

A.3 CCF plots of VIX and TED

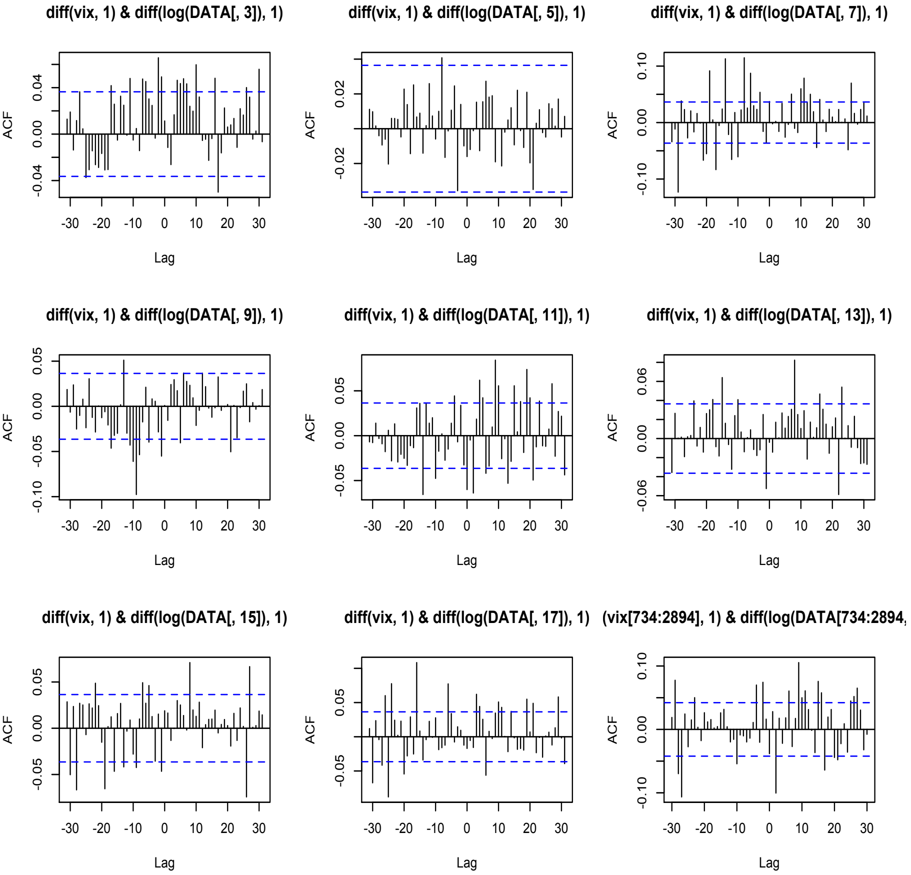


Figure A.1 CCF(VIX) plot of all the currencies. Row-wise, top-left: EUR/USD,JPY,GBP,CHF,AUD,CAD,SEK,NOK,NZD

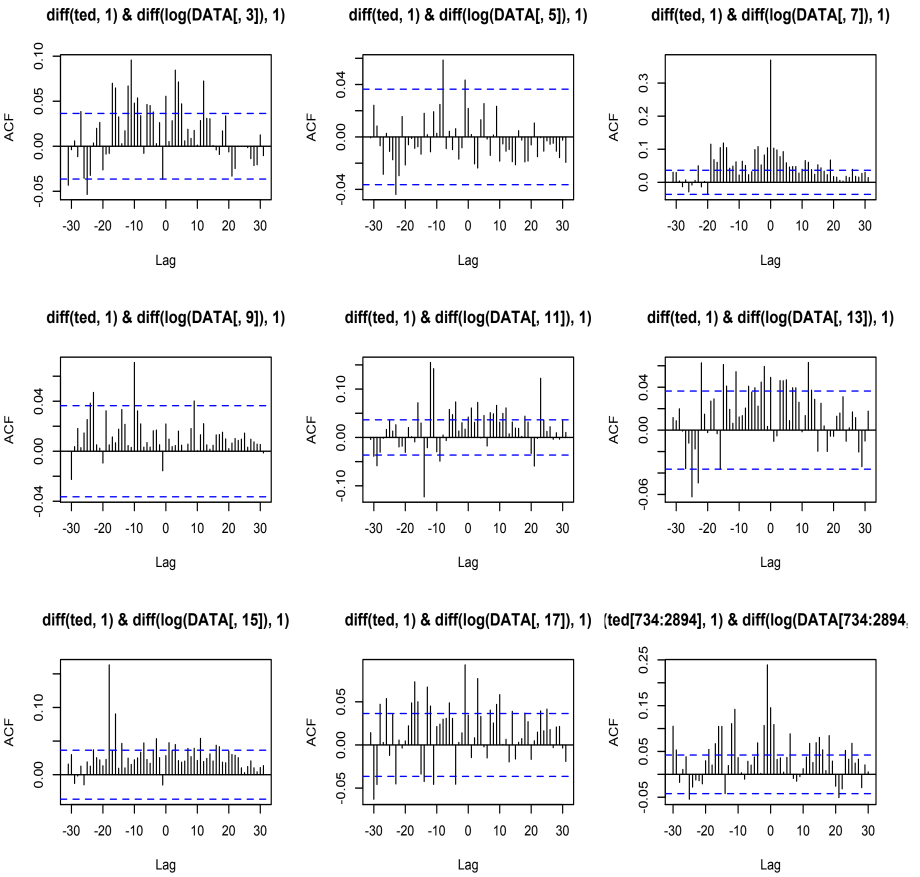


Figure A.2 CCF(TED) plot of all the currencies. Row-wise, top-left: EUR/ USD,JPY,GBP,CHF,AUD,CAD,SEK,NOK,NZD

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